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Investigating the impact of tourism on forest cover in the Annapurna Conservation Area through remote sensing and statistical analysis

A thesis
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Abstract

Tourism is Nepal's largest industry giving people in rural areas an alternative to subsistence farming. Tourism can have an impact on the forest cover of a region as trees provide firewood for cooking and heating and timber for building accommodation. In 1986 the Annapurna conservation area project was started to ensure that tourism was managed sustainably, which includes minimising the impacts on the forest cover. This study assesses the impacts of tourism on the forest cover in the Annapurna region by comparing Landsat images from 1999 and 2011. This was achieved through spectral classification of different land-cover and assessing the change in forest cover in relation to increasing distances from tourism villages. A major problem with remote sensing in mountainous regions such as Nepal is shadow caused by the relief. This issue was addressed by only assessing areas which were free from shadow, which in effect meant a sample was used rather than the whole study region. The results indicate that there has been an 8 per cent reduction in overall forest extent, but this change varies by region. In the northern drier regions there has been a net increase in forest cover, while in the southern regions there has been a net reduction in forests. The influence of tourism facilities on forest is also variable. Around each of the sample tourism villages there was a general trend of decreasing removal of forest at greater distances from each village, which indicates tourism does have a negative impact on forests. However, there was an opposite trend in the northern villages that were well inside the conservation area.

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Chapter 1

Introduction

Tourism provides many opportunities for developing nations to increase their standard of living; however, the tourism industry can also have negative impacts on social and natural environments through degradation of land-cover. Remote sensing provides a method for monitoring the impacts of tourism on land-cover. This thesis examines the Annapurna Conservation Area (ACA) in Nepal as a case study for evaluating the capability of remote sensing. The research draws on the National Aeronautics and Space Administration's (NASA) Landsat archive to detect changes in forest cover between 1999 and 2011.

In the Himalayas a lack of arable land puts great pressure on the ecosystem. Many social and environmental problems are caused by the intensity, by which the land is farmed and resources are harvested. Therefore, land cover changes often have the greatest impact in mountainous regions with high population density such as the ACA. Mountainous regions are also rich in biodiversity with many rare species of flora and fauna, such as the snow leopards or Juniper trees. The biodiversity combined with high levels of erosion and volatile weather creates a very sensitive environment (Stevens, 1993).

1.1 Profile of Nepal

Nepal covers 147,181 square kilometres, of which 75 per cent consists of rugged hills and mountains. The population from the 2001 census was 23.3 million, with a population density of 157.3 persons per square kilometre. Nepalese society is made up of more than a hundred different ethnic groups, which are usually derived from the names of the different languages spoken in different regions of Nepal (Central Intelligence Agency, 2009).



Figure 1.1 Map of Nepal

Due to Nepal's slowly growing economy, the socio-economic state is fragile. Between 2009 and 2010 the target growth for Nepal's economy was 4.5 per cent; however, the actual growth rate was 3.4 per cent. Nepal has great potential to take advantage of its resources in terms of hydroelectric power and tourism but is hindered by the Nepalese government's inability to implement policy and maintain law and order (Government of Nepal, 2012). Poverty in Nepal has always been a significant issue, although the Nepalese government has made progress in reducing poverty. In 1996, 42 per cent of the population were living below the poverty line but by 2010 that number had reduced to 25.4 per cent (The Povertyline, 2012). The quality of life in Nepalese households also reflects the difficult living conditions faced by the Nepalese people. For example, 11 per cent of households have no access to safe drinking water, only 24 per cent of households have electricity and 51 per cent do not have access to food year round (The Povertyline, 2012).

Not only does Nepal have many differences in culture and welfare, it has also experienced many changes in its government throughout much of the last century to the present. Between 1951 and 1959 Nepal began its first experiments with democracy (Central Intelligence Agency, 2009). Most of these early governments were dismissed by the King Mahendra until a system was agreed upon. A four-tiered system of representation was developed, with traditional village councils at the local level, higher levels of representation at district and zonal panchyats and the National Panchayat at the national level. The King, however, held almost unlimited power; he was the supreme commander of the armed forces and exercised control over the judiciary and civil services (Savada, 1991). The government liberalised during the 1980s but was still ineffective due to infighting and corruption. Major reforms during the 1990s transformed the government into a constitutional democracy; however, in 1996 the Maoist conflict began with the declaration of a “peoples’ war” (Library of Congress – Federal Research Division, 2005). Government officials and landlords were accused of causing the economic and political oppression of average Nepalese, and many were killed, expelled and threatened. The conflict ended in 2006 with the signing of the Comprehensive Peace Accord (Central Intelligence Agency, 2009).

In 1951, when Nepal opened its borders to the rest of the world, the largest employer in Nepal was the agricultural industry and at this time tourism was virtually non-existent. From 1965 to 2004 the percentage of Gross Domestic Product (GDP) from the agriculture sector dropped from 65.5 per cent to 40.3 per cent. The decline in agriculture, which was related to the limited use of modern farming equipment and the reduced size of land holdings, caused a decrease food production which, combined with a rising population, has meant that Nepal has not been self-sufficient in its food production since the 1980s. These factors have forced an increasing number of Nepalese to turn to tourism as a source of income. The government has sought to encourage growth in the tourism industry by reducing travel restrictions in some remote areas, by constructing large numbers of tourist centres and by allowing access to 103 mountains (Library of Congress – Federal Research Division, 2005). Over the past 30 years Nepal's political system has affected the tourism industry to experience rapid growth, especially in rural and remote areas. The development of the tourism industry, however, has not

been even across the whole country. The Everest and Annapurna regions are regarded as the most desirable tourism destinations and as a result these regions attract the most tourism consumption. Regions away from these popular destinations are characterised by low income, higher levels of poverty, increased reliance on subsistence farming and out-migration of the youth (Central Intelligence Agency, 2009).

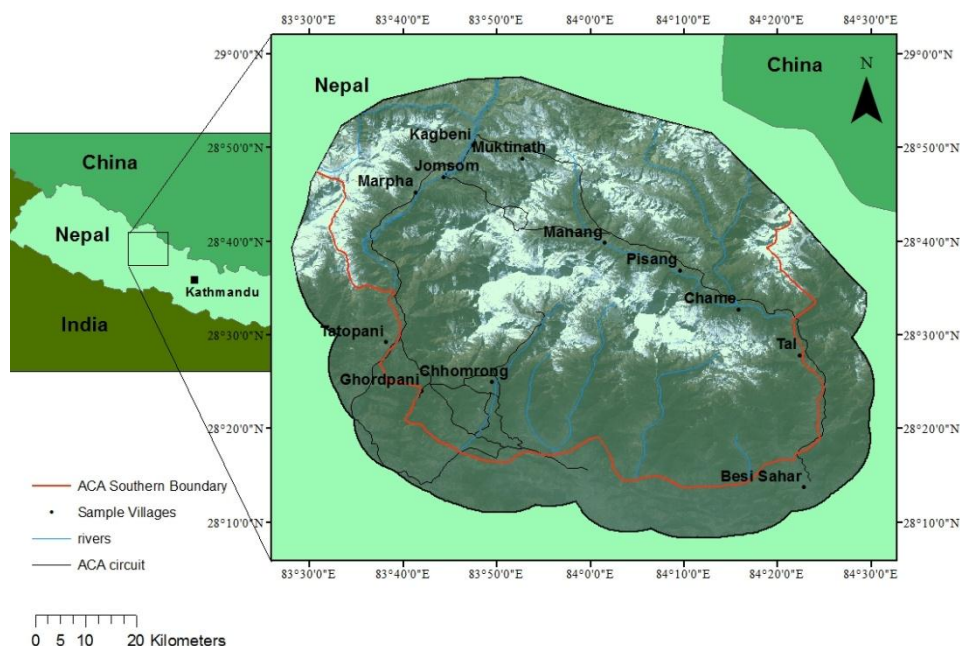


Figure 1.2 Study area: Annapurna conservation area

The Annapurna Conservation Area Project (ACAP) was established in 1986 by the King Mahendra Trust for Nature Conservation. The Annapurna Conservation Area Project (ACAP) was part of an initiative to involve the local population in the management of the (ACA), instead of forcing them to relocate (as is the case with most traditional park management strategies). The ACA consists of 7683 square kilometres and has a population of approximately 100,000 people spread between 300 villages (Mayhew & Bindloss, 2009). The ACAP emphasises environmental education and sustainable economic development. This includes training of lodge owners and the introduction of alternative energy technology, such as kerosene burners and solar panels (Bajracharya, Gurung, & Basnet, 2007). In order to reduce competition and ‘undercutting’, ACAP has also introduced a system which allows for the fixed pricing of goods and services within the region. To manage and oversee the project at the local level, 55 village

development committees were created (Bajracharya et al., 2007). The intention of this was to eventually hand over all responsibility of ACAP to the local population (Chapagain, 2001).

The ACAP has been important to the region because of the many environmental and economic problems the Annapurna region faces. Since historic times the Annapurna Himalaya has been home to a thriving population of ethnically diverse peoples involved in agriculture and trade. The proliferation of tourism has led to a seasonal concentration of around 120,000 tourists who visit the region annually. The increased demand for firewood for cooking and heating as well as for the construction of more than 700 lodges and tea shops has caused localised deforestation (Bajracharya et al., 2007). This has compounded the deforestation that was already a problem in the region before the introduction of tourism (Nepal, 2000).

1.2 The potential of GIS and remote sensing technology for environmental monitoring

Environmental monitoring can be a very time-consuming and expensive undertaking. In mountainous environments such as the Annapurna region, which is both fragile and constantly changing, it is important to keep a continuing record of the state of the environment to ensure the effectiveness of any conservation efforts. Remote sensing offers analysts the ability to keep track of a great variety of natural phenomena on multiple scales over a great length of time. This has all been made possible because of the development of satellite remote-sensing technology during the space race of the 1960s and 1970s (Campbell & Wynne, 2011). However, computer technology has also had an equally large role to play with the development of geographic information systems (GIS) software, which was developed during the 1960s and 1970s (DeMers, 1997). GIS allows researchers to organise, extract and present data from satellite images, as well as to combine data from other sources. In this way, researchers can create maps which show all possible spatial relationships with any particular phenomenon that is being observed (Clarke, 2003). Examples of a widely used remote-sensing system are the satellites Landsat 5 and Landsat 7, which are part of a family of other sensors that all bear the same name. The Landsat program began in 1972,

when NASA, working in cooperation with the US Department of the Interior, launched the trial program: Earth Resources Technology Satellites (ERTS-1). This was the first medium-resolution satellite program designed specifically to gather information on Earth's resources. Researchers from around the world were offered the chance to view the data and NASA was greeted with a very favourable response. NASA renamed the program 'Landsat' and assigned this designation to all subsequent satellites in the program (Lillesand, Kiefer, & Chipman, 2008).

Through ACAP community-based approach to conservation, has been able to preserve the way of life of the villages while encouraging more sustainable tourism practices. Tourist visitor numbers are still increasing and despite the progress made with reducing deforestation within the park there are still a large number of lodge and teashop owners who rely on firewood as fuel and for the construction of new lodges. This is why it is essential for changes in the land cover of the Annapurna conservation area to be monitored so that, if the measures the project has put in place are no longer working, steps can be taken to mitigate further environmental degradation.

Monitoring of the mountain environments, in the Himalayan region, is primarily accomplished by the International Centre for Integrated Mountain Development (ICIMOD): an international organisation whose role is to facilitate the sharing of knowledge between the member countries about the environmental pressures in the fragile mountain ecosystem. Conversely, ACAP is a non-governmental organisation, funded only by the fees tourist pay to get into the park. Therefore ACAP does not currently have the resources or expertise available to ICIMOD to do the same level of environmental monitoring. The research done by ICIMOD is at the cutting edge, using remote sensing and geographic information systems technology. This includes access to the best satellite image data as well as databases from all member nations (International Centre for Integrated Mountain Development (ICIMOD), 2012).

In 2001 an initiative was started to create a GIS-based management information system for the ACAP (Chapagain, 2001). Nawa Raj Chapagain, a GIS analyst at ACAP, is working to establish this database. It is intended to store information on a multiple land-use management system, which classifies the

Annapurna conservation area into five different land-use management zones: wilderness, protected forest/seasonal grazing, intensive use, special management and biotic/anthropological. The GIS database will be able to identify site-specific thematic management options, paying close attention to the needs of the local people as well as the ecosystem of a particular area. However, the system is still in development and local community groups that want research done on land cover change in ACA currently do not have access to a GIS database for the region (Chapagain, 2001).

1.3 Problem statement

If local community groups or ACAP management want to organise and finance a research project to analyse land cover change, the most likely solution in the short term would be to use the free Landsat archive provided by NASA, which is downloadable from the internet (glovis.usgs.gov/). This would greatly reduce the cost of such a project. The next step would be to recruit a GIS analyst who is either a volunteer or a paid professional. Google Earth could also be a source for validation data as well as providing reference data for classification of land cover. What makes Google Earth so useful is that it has a large historical archive of high-resolution images (such as GeoEye) that allows an analyst to look back in time at any location on Earth (Knorn et al., 2009). Landsat images give analysts flexibility in terms of classification and change detection techniques and when combined with GIS software a large variety of spatial analysis techniques are also possible. Depending on the quality of the image, topology of the study site and atmospheric conditions, some techniques are more effective for one site than another, therefore, when performing any remote-sensing analysis, especially in a mountainous area such as the Annapurna conservation area, a number of different techniques would need to be compared in order to get the most accurate results (Chapagain, 2001).

1.4 Objectives

The overall objective of this research is to create a method for mapping forest cover of the mountainous areas in the Annapurna conservation area by using remote sensing and GIS technology. The research was carried out by investigating

a number of classification, sampling and ground-truthing techniques. The analysis focusses on the forest cover change between 1999 and 2011 using images from the NASA Landsat archive. The cause of this change and the various factors contributing to it are also analysed. Through critical discourse analysis, on Nepal's tourism industry, this thesis examines how forest cover change affects the lives of the people and the environment throughout Nepal and specifically in the ACA.

The specific objectives of the research are as follows:

- To detect forest cover change in the Annapurna conservation area.
- To look at the relationship between distance from main tourism centres and the percentage change in forest area.
- To review different methods of image classification and change detection that could be used in future remote sensing environmental monitoring projects set up by ACAP.

1.5 Theoretical perspective

This research makes observations from the perspective of logical positivism. This philosophy has its origins in 1920s Austria and Germany. It is a philosophy primarily concerned with logical analysis of scientific knowledge. Statements about metaphysics, religion or ethics are not assigned any cognitive meaning under logical positivism; only statements about mathematics, logic and natural science (Flynn, 2007). Therefore conclusions made within this research are driven by the results derived from the remote sensing data.

1.6 Structure of thesis

This thesis is structured through seven chapters which explore both the technical aspects of the research and the social and cultural influences of tourism on Nepal and in particular the Annapurna conservation area. Chapter 1 gives an overview of the factors affecting land cover change in the Annapurna region and the importance of monitoring these changes into the future to ensure the conservation

of the environment and culture. Chapter 2 covers a number of areas relating to tourism and land cover change throughout Nepal:

- The influence of mountain tourism on the Himalayan region
- The dynamics of land use and land cover change in Nepal and how those changes have influenced the country
- The Maoist conflict and its influence on tourism
- How the changes in Nepal's recent history may affect the ACA in the future.

Chapter 3 gives a critical analysis of the various remote sensing methods as well as general theory. Chapter 4 is prepared as a stand-alone paper and has been submitted to the Journal of Applied Geography for peer review. This chapter includes an abbreviated introduction and literature review as well as the method, results and a condensed discussion and conclusion. Chapter 5 discusses the results and analyses the causal factors that influenced the results, a critical review of the method and recommendations for future research. Chapter 6 includes a restatement of the research objectives and how successfully they were achieved, the implications of the methodology on geography and remote sensing research and finally the implications of the findings for tourism and conservation in the ACA.

Chapter 2

Tourism and land use in Nepal

2.1 Overview

This chapter reviews the literature on studies of the impact of tourism on the environment and information relating to the people of the Himalayas. The chapter will discuss the land use characteristics throughout Nepal with a particular emphasis on the Annapurna Region. The culture and recent history of the Annapurna region is also examined in this chapter in terms of how the region has changed due to tourism. Lastly this chapter will discuss the importance of environmental monitoring to keep track of the negative effects of tourism and how the local community is becoming more involved in the management of the conservation area.

2.2 Studies on mountain tourism in the Himalayas

In 1998 a study by the International Centre for Integrated Mountain Development (ICIMOD) looked into the issues in terms of development policies involving rural development for tourism purposes. The study explored ideas that could invigorate the development of tourism in the mountain regions of the Himalayas. The issues that needed the most attention were:

- Energy technologies
- Carrying capacity
- Sustainability
- Participatory community-based approaches to management
- The requirements needed in order to monitor any system of tourism development.

The objective of this study is to introduce regional authorities and developers to these concepts and to generate an awareness of the importance of these issues so that the creation of sustainable mountain tourism operations can go ahead. The

paper makes the point that creating sustainable rural tourism development using a community-based approach can help facilitate initiatives such as poverty alleviation, environmental care and empowerment of local populations (Banskota & Sharma, 1998).

2.2.1 Energy technologies

Energy technology is an important factor in mountain tourism. In 1997 ICIMOD produced a manual that illustrated the role that energy technology plays in tourism. The objective of the manual was to establish methodologies for applying energy technology to the tourism industry not only in mountainous areas but throughout the industry. Some of the applications explored in the manual included: energy for lighting, space heating, cooking, medicine and waste management. The manual talks discusses how the tourism industry is growing exponentially in Nepal and how trekking is one of the largest parts of that industry with the numbers of trekkers visiting the country increasing by 17 per cent annually (Maharjan, Pelinck, & Shrestha, 1997). The manual cites a number of benefits that the use of energy technology has already contributed to the tourism industry; for example, there is less dependence firewood and timber or imported fuels, more sustainable use of local resources, more control over environmental degradation, increased agricultural productivity, better sanitation, better working conditions and more satisfied tourists. This has led to higher tourist flow and increased income for tourism operators (Maharjan et al., 1997).

2.2.2 Carrying capacity

When looking at how mountain tourism can be improved, an important aspect to consider is the carrying capacity of any particular area. In 1995 a study was produced on a framework for tourism carrying capacity (Sharma, 1995). The study indicated that there were certain factors that influence carrying capacity such as:

- Isolation of the region
- Fragility of the natural resources
- The number and variety of tourist attractions

- The number and frequency of visitors
- Quality of maintenance of infrastructure
- The level of resource use management
- The attitudes of both the local people and the visitors in relation to each other and the environment.

Another aspect of carrying capacity raised in the report considers that development in mountainous regions is often marginalised by central government and regional authorities. Thus, if people in isolated rural mountain communities want to develop tourism operations they need to fund and motivate any effort to do so themselves.

A major factor in determining carrying capacity is the management of natural resources. One of the best ways to monitor how natural resources are being used is to look at the biodiversity of a region. In 2008 ICIMOD, the Global Mountain Biodiversity Assessment (GMBA) and Global Biodiversity Information Facility (GBIF) held a workshop in order to address the issue of how best to organise and display biodiversity information. The paper, which was written for the workshop, outlined that biodiversity information was essential to policy making and resource management strategies as well as the development and testing of any hypotheses about interactions in the natural world (Spehn & Shrestha, 2008). The purpose of the workshop was to show how effective geo-referencing biodiversity data with other geo-located data such as climate or land use could be. The importance of mountainous regions, such as the Himalayas, was also discussed. The paper explained that mountainous regions of the world only cover one fifth of the global land area, yet they contain 4 per cent of all vascular plant species. Based on some estimates that the total number of vascular plant species is 420,000 (Jørgensen et al., 2011). Four per-cent of that number amounts to 16,800 which means that on average in mountain regions there will be 16,800 different vascular plant species, making mountainous regions hotspots for plant biodiversity. Some of the recommendations to come out of the workshop were that ICIMOD should become a regional node for GBIF and that ICIMOD should facilitate key national partners to become national nodes for GBIF in their own regions. The purpose of the paper was to promote a common

methodology and databases for the geo-coding of biodiversity information (Spehn & Shrestha, 2008).

2.3 Land use throughout Nepal and in the Annapurna conservation area

In Nepal the land is divided into three separate landforms which define the landscape from north to south. Located in the south are the plains known as the Terai which are dominated by various wheat, rice and maize crops. Beyond the Terai is the central hill country that has both tropical and temperate broadleaf forests with terraced farms and many hydroelectric dams of various sizes in many of the valleys. Bordering China are the high mountain valleys before the Tibetan plateau. The land cover in these areas varies from conifer forest, alpine pasture and alpine desert. Vegetation cover, in the high mountain valleys, changes depending on their orientation. Valleys which face toward the north tend to be in rain shadows and are therefore a lot drier than south-facing valleys (Central Intelligence Agency, 2009).

A study conducted by the Nepalese Ministry of Forestry and Soil Conservation in 1998 looked at the extent of deforestation between 1964 and 1979 throughout Nepal. The study found that from 1964 to 1965 the crown cover of the forests reduced from 70 to 40 per cent and by 1979 it was found to be 13 per cent. Some of this deforestation was in the lower plains but the majority of deforestation was located in the middle and higher mountains of the Himalayas (Joshi, 1998). Tourism, trekking and mountaineering, between the 1960s and 1980s escalated in Nepal, bringing more people into the middle and high hill country to support the tourism industry. It also resulted in increased clearing of land to support the growing population there as well as the influx of tourists. In 1965 the Terai region was cleared of malaria, promoting migration to the region and clearing of land for agriculture. These contributing factors - combined with a rising population across all of Nepal - put major pressure on Nepal's forest resources (Joshi, 1998).

Several factors have influenced the settlement and growth of urban areas throughout Nepal. In 1951 the country opened its borders to international visitors.

This also opened the way for foreign investment in infrastructure. New roads, bridges and dams started to be built, helping to increase the growth of towns and villages. The eradication of mosquitos in malaria-prone areas of the southern Terai plains paved the way for the resettlement in the region of many people from in the central hill country and beyond (Basyal & Khanal, 2001). As tourism became more popular during the 1970s and 1980s, regions around Annapurna, Everest and Chitwan National Park (a World heritage-listed forest park that shares part of its boundary with the Indian border) experienced urbanisation. The development of tourism prompted inflows of people coming to find either permanent or seasonal work in the industry (Kruk, Kreutzmann, & Richter, 2011). During the Maoist conflict between 1995 and 2006 people flooded into major cities such as Kathmandu and Pokhara to escape the violence in some of the rural regions, thus greatly expanding the populations of these cities. By some estimates, urbanisation in 2000 had increased to about 15 per cent of the population which amounted to more than 3 million people (Basyal & Khanal, 2001).

Annapurna conservation area is just a small corner of this large and diverse country, but it is a good example of an area which has been set aside for conservation and one which still retains a local human population, 102 mammalian species and 488 bird species (Bajracharya et al., 2007). The climate in the ACA is greatly influenced by its altitude and the monsoon season, in turn dictating what vegetation grows where. Altitude creates a rapid succession of different forest types at various heights (Department of National Parks and Wildlife Conservation, 2012). Around 1000 metres temperate and tropical broadleaf tree species such as oak or alder are more dominant, however, beyond 2000 metres conifer tree species such as blue pine, fir and juniper are more common. The monsoon season creates rain shadows in north-facing valleys, while south-facing valleys receive high levels rainfall creating perfect conditions for lush, dense forest. In the southern parts of the ACA these are largely dominated by rhododendron trees. The north-facing valleys are vastly drier, reducing the density of forest cover. In some areas of the northern parts of the ACA, for example near the village of Muktinath, the forest disappears all together and becomes a mixture of grassland and desert. Erosion is also a major factor due to high rainfall in south-facing valleys, extremes of temperatures at high altitude and

high winds, particularly in the Kali Gandaki Valley (Mayhew & Bindloss, 2009). These environmental factors combine to create a challenging and dynamic place for people to live. The land uses that define this region are mostly agriculture and animal husbandry but many people are also employed by various government services. Although there are programs to mitigate various negative impacts of tourism and agriculture, in this region, there are still environmental and cultural issues that continually need addressing. These include deforestation, biodiversity loss, eroding indigenous knowledge and practices, poverty and lack of resources. Some of the programs to address these issues include: natural resource conservation, alternative energy, agriculture and livestock development, tourism development and gender development, as well as community development and capacity building (CAMCs) (Bajracharya et al., 2007).

2.4 The influence of tourism on people and the environment in the Annapurna region

Tourists have been coming to the Annapurna region for trekking and climbing since the 1950s (Chris & Bonington, 1973) but tourism did not really take off until the 1970s, when counterculture began descending on Pokhara, Nepal's third largest city and the gateway to the region. As discussed in Chapter 1, the Annapurna conservation area was formed in 1986 by the King Mahendra Trust for Nature Conservation to control the growth of the industry in the area and mitigate the environmental damage it caused (Mayhew & Bindloss, 2009).

The influence of the establishment of tourism on the people of the Annapurna region can be illustrated by the Gurgung and the Thakali people, which are two of the largest ethnic groups in the Annapurna region (Bista, 1967b). The Gurgung people are found mainly in the Manang valley. Their economy is mostly based on agriculture, which includes sheep breeding and growing various crops such as rice, wheat, maize, millet and potatoes. With the introduction of the tourism industry, however, economic practices have diversified (Bista, 1967b). Some residents have become lodge and teahouse owners but the vast majority have become porters carrying supplies for trekkers. The Thakali are located mainly in the Kali Gandaki Valley north-west of Pokhara. These people were once involved in the salt trade as they have exclusive rights to Himalayan salt, but

heavy government taxes on these rights forced many to move into agriculture as well as long-distance trade and investment in land and other businesses. Over the last century the Thakali have become a wealthy group within Nepalese society. Thakali people are now in more of a position to take advantage of the growth in the Annapurnas tourism industry and to control enough capital to start businesses with relative ease as well as to own large amounts of land (Bista, 1967b).

Tourism has also affected the economic disparity of the region. People living in areas along the main trekking routes that pass through the villages of Manang, Jomsom and Annapurna base camp all have higher income, education and employment opportunities. For example, there are some 50,000 guides, porters and other service providers employed in tourism, living in and around those three settlements. The region has also experienced an almost exponential rise in tourist visitor numbers; between 1980 and 2003 annual visitor numbers increased by 50, 668 (Nepal, 2008).

It has been estimated that 85 per cent of the world's energy consumption is derived from fossil fuels (Nepal, 2008). Like all industries the tourism industry has always required a certain amount of energy use to sustain its growth. In the Annapurna region the story of energy use by the locals has been typical of a people who have only recently become part of the modern world. The local peoples have relied on firewood for their own energy needs for many years before tourism came to the region. They only started to change their energy use with the introduction of ACAP which as mentioned in the introduction promoted the use of alternative energy technologies (Nepal, 2008).

Table 2.1 Differences in per-tourist average daily energy consumption (Nepal, 2008)

Energy sources (unit)	Annapurna BC		Jomsom		Manang	
	Energy consumed per person	% lodges using	Energy consumed per person	% lodges using	Energy consumed per person	% lodges using
Fuelwood (kg)	4.40	66.4	4.90	82.4	5.30	82.7
Kerosene (L)	0.77	93.2	0.41	79.8	0.35	86.7
LPG (no. of tanks)	0.07	22.8	0.02	10.3	0.02	9.0
Backboiler		24.6		53.8		38.4
Solar water heater		31.9		38.1		17.0
Hydroelectricity		45.9		76.2		84.1

Table 2.1 shows how the different types of energy technology introduced by ACAP have diversified energy use throughout the Annapurna conservation area. It also shows the variation of energy use that is dependent on access and cost of certain energy sources. Though firewood is no longer the sole source of fuel it is still used to a degree throughout the region, especially in the more isolated areas that are at altitudes where vegetation still grows.

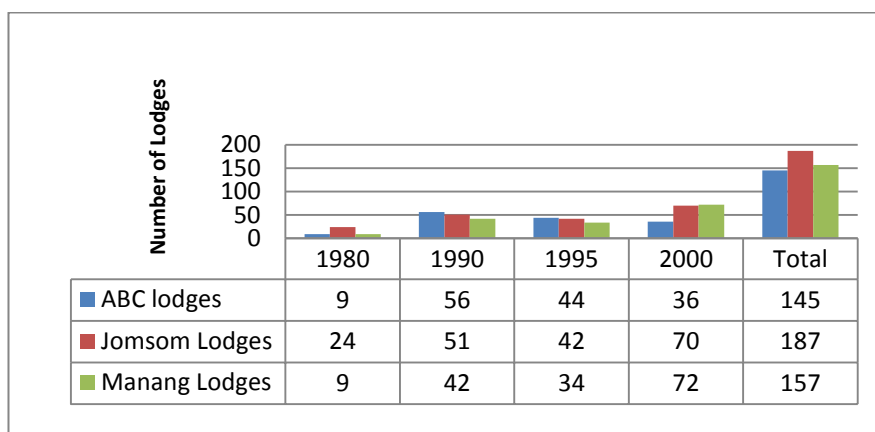


Figure 2.1 Growth in accommodation capacity in Annapurna
(data for this figure obtained from Nepal, 2008)

Energy use is not the only factor to consider. Figure 2.1 shows one of the other pressures on forests in the ACA, which in this case is harvesting timber for the development of tourism infrastructure. From 1980 there has

been fluctuating development throughout the region with some decline in development in 1995, which picks up again in 2000. During field work for this research, evidence of continual development of new lodges in the Manang valley, in the village of Muktinath and in the Annapurna sanctuary was seen (see figures 2.2, 2.3 and 2.4).

- In the Manang valley there was logging camps and pit saws that are designed to shape harvested timber into planks.
- In Muktinath there was a lot of construction of new buildings some of which may have been lodges.
- In the Annapurna sanctuary during most days of field work in that part of the ACA porters were seen carrying large planks between the villages further up the valley for the construction of new lodges.



Figure 2.2 Image of a pit saw in the Manang valley near Chame (Image taken during field work)



Figure 2.3 Image of road works on the main street of Muktinath (image taken during field work)



Figure 2.4 Picture of a place porters unloaded timber for building lodges in the Annapurna Sanctuary (image taken during field work)

All this resource use could have potentially cause major environmental problems in terms of forest degradation as well as in other areas such as human waste management and so on. Some research has shown that the forest density inside the Annapurna conservation area is much higher than it is outside; and the diversity of plant and animal species is also greater inside than outside the ACA. This factor is not to be overlooked due to the collective efforts of the community becoming directly involved with conservation management inside the ACA. An example of some of the progress made by the community groups in the ACA is the planting of 1,666,000 seedlings between 1986 and 2000. It is efforts like this and others that have preserved the landscape, culture and ecosystem in this diverse and beautiful part of Nepal (B.Bajracharya, Furley, & Newton, 2005).

2.5 Land development theory in relation to Nepal

Land development and resource use follows certain patterns that are influenced by market forces. In 1826 Von Thünen published a theory that explains how land use patterns around a single marketplace are influenced by transport costs (Mather, 1986). The theory states that at greater distances from a market, farming becomes less profitable. This is due to the increasing cost of transport to the marketplace and the higher cost of labour at greater distances from the marketplace (Mather, 1986). A study on the effect of road development in rural Nepal indicated that land values in areas that were in close proximity to new roads increased significantly (Jacoby, 2000). Another study that reviewed Von Thünen's theory in relation to land development in a number of countries – including Nepal – showed that as the profit from land increased, deforestation also increased as it became more affordable to clear land for farming (Luca, 2007). Although Von Thünen's model does not account for things such as climate, soil condition or relief of the land (Luca, 2007), it is nonetheless relevant to the Annapurna region as extensive road development was seen in many parts of the Annapurna circuit during field work. It is therefore conceivable that the roads could bring in more resources to the region as well as bringing tourists to other villages, generating more profit for tourist operators and farms and putting greater pressure on local resources.

2.6 The Maoist conflict and Nepal's tourism industry

The Maoist conflict in Nepal occurred between 1996 and 2006. It was termed 'the People's War' by the Communist Party of Nepal, which fought on the basis that they were fighting to change the socio-economic and political structure of the country. The war cost 15,000 Nepalese lives and displaced some 200,000 people (Upadhayaya, Müller-Böker, & Sharma, 2011). Nepal's tourism industries reputation suffered during the war. However tourism in Nepal is a relatively recent phenomenon. Most of the industry was monopolised by the wealthy and political elite such as the feudal houses of the Ranas and the Shahs. Once more, most of the tourism activity was concentrated between Kathmandu, Pokhara and Chitwan. This created an imbalance of wealth and income from the industry. The effect of this was to make a large part of the tourism industry targets for the Maoists; it was their contention that the Ranas and Shahs were obstacles to their revolution as they represented the old, privileged elite of society (Upadhayaya et al., 2011).

Matters were complicated further when King Birendra and his family were killed in June 2001, after which Gyanendra Shah ascended the throne. King Gyanendra Shah then escalated the conflict, labelling the Maoists terrorists, which prompted the United States to follow suit. This created a lot of anti-American sentiment among the Maoists. Consequently, American visitors were targeted by the Maoists, thus greatly reducing the amount of American visitors in particular. The Maoists had a policy of only targeting American tourists and tourism owners and operators who had a connection to the Ranas and the Shahs. All other tourists were left alone; overall, there were no recorded tourist fatalities caused by the conflict. The negative impacts were mostly to do with loss of revenue, decreased visitor numbers, reduced quality of service and an increased level of fear and uncertainty in tourism business owners and operators (Upadhayaya, Müller-Böker et al., 2011) In 2006, the conflict ended and the Nepal Communist Party officially became part of the government. While doing the field work for this research, the different factions of the government – including the Maoists – were working together to form a new constitution. With an unstable government sustainable development of the tourism industry in the ACA may prove challenging if another conflict breaks out.

2.7 Future prospects for ACAP

The Nepalese government, in common with many developing countries, adopted community-based conservation for many of its parks because of bad relations with the residents of the parks. A study published in 2001 indicated that communities living and working inside or near national parks and conservation areas in Nepal had a great variety of opinions on how they viewed the park in their region (Mehta & T.Heinen, 2001). In Annapurna conservation area 400 people were surveyed and some 85 per cent felt that the creation of the park was for the betterment of their community. Participants were also asked what factors made them have this positive attitude. Of the programs people liked, 59 per cent thought the community forestry was a positive aspect of the conservation area, 44 per cent liked the community development programs, 30 per cent wildlife conservation, 26 per cent the creation of awareness of the ACA environmental problems, 10 per cent liked the economic benefits of tourism and 6 per cent valued the training programs for tourist operators (Mehta & T.Heinen, 2001). This profile of public opinion indicates that the people of the ACA will continue to have positive attitude towards the conservation while they are involved in the management of the ACA, as well as education in sustainable business and environmental practices.

The continued presence of tourism in the Annapurna region also brings further development of infrastructure. During field work of this research it was discovered that there were a number of road-building projects inside the ACA. There seemed to be many mixed views as to how this would change the landscape and the livelihood of the people living there. One prime example was the road under construction in the Marshyangdi river valley all the way up to the start of the Manang district in Tal, which is the centre of administration for the lower Manang district. So far the road in this region has allowed extra supplies and other resources to move more freely up the valley in Jeeps and trucks. Tourists are also increasingly taking buses as far they can get by road up the valley. Farmers in the region gain more access to alternative energy sources such as kerosene as well as farming equipment. For some tourism operators it means they can have a larger turnover of guests coming through the area, creating more revenue for local business. In the case of Bahundanda, a village that is bypassed by the road, there has been a drop in business over the years as a result, and some residents may

need to move to villages on the main route of the track. In other regions such as the Kali Gandaki Valley, roads have been established and maintained for many years permitting impressive levels of infrastructure to be built in places like Muktinath and Jomsom including airports, power stations, large bridges and telecommunications.

The building of roads in these kinds of environments, where people live relatively sheltered lives and are not accustomed to the dangers of cars, one outcome is that road fatalities are relatively common. Road infrastructure also changes the aesthetics of the region, making it less popular by trekker's standards. An increase in development affects an increase in the region's population, with the potential to put a greater strain on the limited resources available in the alpine environment. It is difficult to specify exactly how this kind of development will affect the economy and environment of the Annapurna conservation area but it is clear that equilibrium will need to be reached. That is why continual monitoring of the environment into the future is necessary; as the region changes, the efforts made by the local committees and administration of the ACAP may not always be enough to mitigate the environmental and culture degradation that comes with increased development of infrastructure and growth of the local economy.

Chapter 3

Remote sensing and change detection theory

3.1 Overview

This chapter provides a critical review of remote sensing (RS) theory and change detection methods for mapping forest cover. First, the basic principles of RS are described including the nature of electromagnetic radiation (EMR), reflectance and emittance, image capture and image resolution specifications. This is followed by image preparation, which includes correction for geometric and atmospheric distortions, conversion to digital numbers (DN) data, and enhancement using false colour composites and normalised difference vegetation indices (NVDI). A review of image classification and error assessment methods is then provided. The last part of this chapter describes methods for change detection.

3.2 The nature of electromagnetic radiation and image capture

Remote sensing is loosely defined as “the science and art of obtaining information about an object, area or phenomenon through the analysis of data acquired by a device that is not in contact with the object, area or phenomenon under investigation” (Concepts and Foundations of Remote Sensing: Introduction Lillesand et al., 2008, p. 1).

3.2.1 Electromagnetic radiation

Remote sensing uses a variety of methods for obtaining data. These can include variations in force, acoustic waves and electromagnetic (EM) energy. For humans, all that can be seen of the EM spectrum is visible light. However, visible light occupies only a fraction of the EM spectrum, which also includes radio waves, heat, ultraviolet rays, X-rays and others. Basic wave theory describes EM radiation as “travelling in a harmonic, sinusoidal fashion at the velocity of light”

(Concepts and foundations of Remote Sensing: Energy Sources and Radiation Principle Lillesand et al., 2008, p. 4).

The largest source of EM radiation in our solar system is the sun; however, radiation is also emitted or reflected from all surfaces that are above absolute zero or -273°C (Lillesand et al., 2008). Remote sensing can be used to analyse the differences in the radiation emitted or reflected from objects or phenomena on Earth to provide information on features of interest.

The energy produced by the sun is not constant across all wavelengths within the EM spectrum (Gibson & Power, 2000). This is important for remote sensing, as the shorter and longer wavelengths of the EM spectrum are absorbed by the upper atmosphere, allowing only certain wavelengths to reach the Earth's surface. It is these parts of the EM spectrum that are not absorbed by the atmosphere which are called "atmospheric windows" (See Figure 3.1).

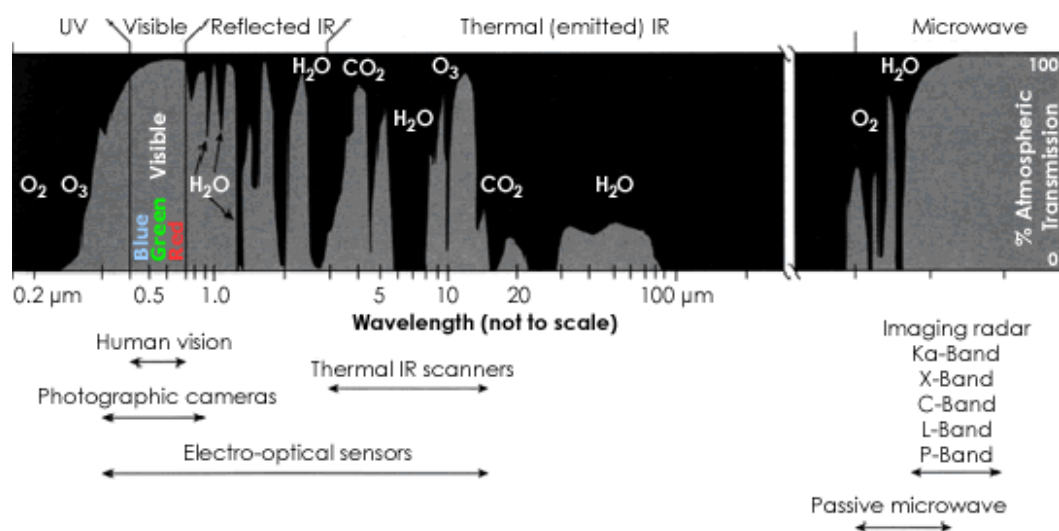


Figure 3.1 Spectral characteristics of atmospheric transmittance (King & Herring, 2012).

EM radiation or light interacts with objects or phenomena in a variety of ways depending on the wavelength within the EM spectrum and the feature that it is interacting with. There are four ways in which EM radiation interacts with features in the environment: reflection, absorption, scattering and transmittance. These principles are defined as follows:

- Reflection is when EM radiation is rebounded from an object or phenomenon.

- Absorption is when a portion of EM radiations energy is taken up by the matter that it hits, transforming the energy in most cases into heat.
- Scattering refers to instances where certain wavelengths of light are displaced and redirected by particles such as dust in the atmosphere.
- Transmittance is about light passing through a medium with some bands within the EM spectrum being absorbed by that medium. The atmosphere is an example of such a medium and atmospheric windows, referred to previously, are examples of atmospheric transmittance, which is the wavelengths of the EM spectrum that can pass through the atmosphere (Lillesand et al., 2008).

The spectral responses of different features to EM radiation measured by remote sensing instruments are referred to as spectral signatures. The spectral signatures of different features can be graphed and used to identify the wavelengths of EM radiation that are the most effective for detecting certain features on the ground, such as vegetation or water (see Figure 3.2).

Vegetation appears green because the chlorophyll absorbs the blue and red wavelengths of the visible spectrum and reflects much of the green light. The amount of chlorophyll within plant cells decreases when they are under stress, reducing the absorption of the blue and red energy to the point where the reflectance of red light is high enough to make the plant appear yellow. Leaf structure is important because the highly variable structures of various plant species produce different reflectance values (Lillesand et al., 2008).

The reflectance characteristics of water depend primarily on whether it is in a solid or liquid state. Snow and ice are highly reflective in the visual bands but liquid water has low reflectance in the visible range and very little in the near-infrared bands. The reflectance of water is also influenced by its depth and content; for example, the amount of chlorophyll in water can alter the amount of blue and red light absorbed, which changes how green a body of water looks. Soil reflectance is complex because it is influenced by mineral content, moisture levels and surface texture (Gibson & Power, 2000).

Figure 3.2 shows how conifers, soil and water have varying levels of reflection within the spectrum. For example, conifers reflect highly in the near-infrared bands from 0.7 to 1.3 μm , which is due to leaf structure and chlorophyll content. The reflectance of soil only surpasses vegetation features such as conifers at 1.4 μm ; it peaks at 1.9 μm and starts to tail off after that point.

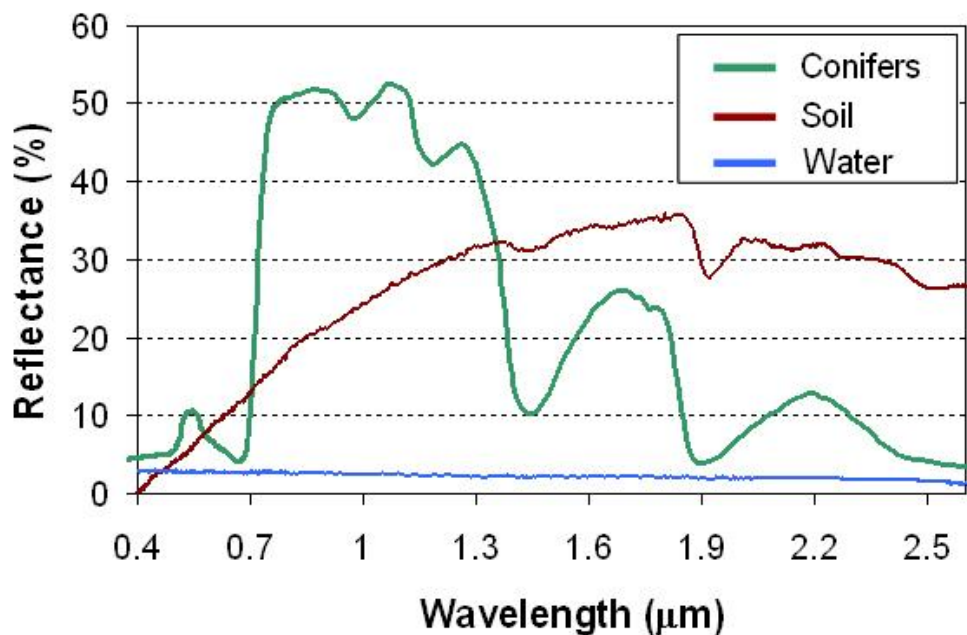


Figure 3.2 Spectral signatures for conifers, soil and water (EUMeTRAIN, 2010).

An example of a satellite that captures spectral signatures is Landsat 7. Landsat 7 sensors detect seven different bands within the EM spectrum. This ranges from visible light to mid-infrared light. This allows Landsat 7 to distinguish a variety of spectral signatures that represent various land-covers and conditions on the earth surface. This includes many vegetation types, mineral types and cultural features as well as temperature, moisture levels and the condition of plants (Lillesand et al., 2008).

3.2.2 Active and passive sensors

There is a great variety of remote sensing platforms; however they can be divided into two groups: passive and active sensors. Passive sensors use EM radiation that is either emitted or reflected from the objects or phenomena being observed (Gibson & Power, 2000). Passive sensor platforms include aerial photography and land observations satellites, one example of which is the Landsat family of

satellites. The Landsat satellites come in two types: multispectral scanner subsystem (MSS) and thematic mapper (TM). The difference between MSS and TM is that the TM sensors are more sophisticated and produce less error in the data. Passive sensors are also capable of producing thermal images by unitising spectral bands in the infrared range (Campbell & Wynne, 2011).

Active remote sensing platforms transmit EM radiation signals and use the returning signal reflected off the observed object or phenomena. Active sensors are used in situations where an analyst is trying to observe features in an environment where emitted or reflected EM radiation cannot be captured; for example, the sea floor or through dense atmosphere (Campbell & Wynne, 2011). In that situation a sensor that emits microwave radiation is used, as that part of the EM spectrum can be transmitted through dense atmosphere and water. Another example of an active sensor is light detection and ranging (LIDAR), a system that is normally installed on an aircraft and projects a laser that produces a highly detailed map of the surface from the laser's reflections (Lillesand et al., 2008).

3.2.3 The importance of resolution in remote sensing

A common application for remote sensing data is land-cover classification and change detection. This involves looking at images over a certain period of time at a particular location or region and classifying the different features of that landscape. Remote sensing data can give coverage over many landscapes and many years, which creates the opportunity to document changes in the environment over time (Gibson & Power, 2000). Of course this requires two or more images with similar resolutions. There are three types of resolution that need to be considered: spatial, spectral and temporal resolution (Jensen, 2005).

- 1 Spatial resolution is the sensor's ability to distinguish objects or areas at various scales. For example, Landsat 7 has a spatial resolution of 30 m, which means each cell in its image represents 30 m by 30 m on the ground (Jensen, 2005).
- 2 Spectral resolution refers to the capability of a sensor to determine different features based on how many different spectral signatures it can identify (Lillesand et al., 2008).

- 3 Temporal resolution depends on how often a recording of an area can be made by a sensor; for example, Landsat 5 comes back to the same point every 16 days. This can influence the type of phenomenon that the sensor is suitable for detecting (Gibson & Power, 2000).

3.3 Principles of image preparation and image enhancement

Remote sensing studies involve a specific process that starts with the statement of a problem then moves through the collection of data to the conversion of that data into information, which is then modified further for presentation (Jensen, 2005). Data is collected using a sensor to record the differences in EM energy that are either reflected from or emitted by the surface areas of interest (Gibson & Power, 2000).

3.3.1 Conversion of data

The conversion of data into information, otherwise known as image analysis, involves examining the remote sensing data using various interpretation techniques (Jensen, 2005). These can be categorised into three types: visual techniques (Bhattarai, Conway, & Yousef, 2009), computer-based techniques and a combination of the two (Sader, Ahl, & Liou, 1995).

- 1 Visual-based image interpretation is an analogue form of analysis that relies on the ability of the human mind to recognise patterns within an image that represent certain objects or phenomena and to judge their significance (Jensen, 2005). This can be very time consuming, often involving a stereoscope (Lillesand et al., 2008).
- 2 Computer-based or digital image-processing interpretation has several advantages over visual interpretation. Firstly, it allows the difference between the different spectral signatures to be graphed and visualised so that comparisons can be made. Secondly, the processing of images can be mostly automated, making it more efficient to process large numbers of images. Finally, there is a great variety of analysis and image enhancement techniques (Jensen, 2005).

- 3 A combination of visual interpretation and computer technology techniques can also be informative. For example, in 2007 research carried out in the Carpathian Mountains used stereo interpretation of images from Landsat, QuickBird, Spot, LIDAR, and a digital elevation model (DEM) of 1 metre, and aerial and oblique photos taken in the field. The purpose was to classify land-covers and landforms looking for environmental indicators of changes in biodiversity and sensitivity of certain areas to hazards such as flooding and erosion (Granica, 2007).

3.3.2 Image correction

Remote sensing systems often have errors occur during the recording of the data. These errors can come from distortions in the atmosphere, loss of signal from the sensor to the receiving station, corruption of the data or malfunction within the sensor itself. Whatever the source of the errors, it is essential to correct them before any image analysis is performed (Gibson & Power, 2000).

3.3.2.1 Topographic correction

Topographic correction compensates for the effect of variations in the morphology of the land in relation to the position of the sun. It is the relationship between the sensor–sun–land geometry that creates shadows over the land within satellite images.

The methods used to achieve topographic correction are either Lambertian or non-Lambertian, which refers to whether a surface is a perfect reflector when viewed from all angles (Law & Nichol, 2004). An example of a Lambertian method is the cosine correction, which assumes the surface is Lambertian and only attempts to correct the differences in illumination created by the shape of the land. This method tends to over-correct due to the Lambertian assumption. A non-Lambertian method is the Minnaert technique, which is a photometric function referring to photometry the study of the sensitivity of the human eye to radiance at each wavelength in the EM spectrum. The algorithm uses a constant value symbolised by “ k ” that is between 0 and 1. This value is a test of whether the surface in an image is Lambertian or not. If it is Lambertian, then k equals 1; if it is not, then k is less than 1 (see equations 3.1 and 3.2). As this method does

not use the Lambertian assumption it has a tendency to under correct (Law & Nichol, 2004).

$$\cos \cos i = E \cos Z + \sin E \sin Z \cos A - AS \quad (1)$$

$$Ln(\lambda) = L(\lambda) / \cos i \quad (2)$$

$$\cos / \cos HTL = L z i \quad (3)$$

Where:

L = radiance

Z = solar zenith angle

LH = radiance for horizontal surface

LT = radiance observed over the inclined terrain

i = incidence angle with respect to surface normal

E = slope inclination

Z = solar zenith angle

AO = solar azimuth

AS = surface aspect of the slope angle

Equation 3.1: Lambertian algorithm: the cosine (Law & Nichol, 2004)

$$L(\lambda, e) = Ln \cos^{k(\lambda)} i \cos^{k(\lambda)-1} e$$

Where:

L = radiance

λ = wavelength

e = slope angle

Ln = radiance when $i = 0$

k = Minnaert constant

i = incidence angle

Equation 3.2 : Non-Lambertian algorithm: the Minnaert equation (Law & Nichol, 2004)

Both of the above methods also required digital elevation model (DEM) to extract spatial information about slope and aspect relating to the incident angle of the sun. When choosing a DEM for a topographic correction it is recommended that the DEM either has the same or greater spatial resolution that the remote sensing image to ensure the best results. Unfortunately even when the DEM has the same resolution errors can still occur (Nichol & Hang, 2008).

The other possible method for correction of shadow caused by topography is the use of interpolation and masking techniques that are often used to filter out clouds. The first step in this process is to convert a multispectral image into a thermal image. The next step is to identify the pixels that appear as clouds and shadow within the histogram of the thermal image data. The selected shadow and cloud pixels are used to generate a mask of the areas that are not cloud or shadow and this is used to filter out the regions of cloud and shadow in a multispectral

image of the hypothetical study area. The last step is to fill in the missing data by using an interpolation called “kirting” (Silva, 2011). The down side of this process is that the data that is put into the gaps produced by the filtering process is only based on the data surrounding it. Therefore such data may not be reliable.

3.3.2.2 Geometric correction

Satellite images are often not projected correctly to a defined coordinate system. This is known as a geometric distortion or error and the process of correcting these errors is known as geometric correction. Geometric distortions can be either systematic or non-systematic. Systematic distortions are those that apply to images that come from a specific remote sensing platform, whereas non-systematic distortions apply to individual images (Gibson & Power, 2000). There are many sources of systematic error but two common ones are the movement of the Earth in relation to where the satellite is scanning as well as differences between the speed of the scanning mirror and the forward velocity of the satellite. Many systematic errors are corrected before getting to the end user by using data derived from monitoring a satellite’s orbital path as well as having information about the satellite’s characteristics. Non-systematic errors often result from differences in the orbital height of various systems as well as the changes in orbit when the satellite pitches, rolls and yaws (Gibson & Power, 2000).

There is a great variety of methods used but many of them are based on two different models (Mather, 2005). The first is the orbital geometry model. This model is based on having knowledge of the characteristics of the orbit of the remote sensing platform. The equations used in this model relate the coordinate system of the image to a geographic coordinate system suitable for the study area (Mather, 2005). The second model uses transformations based on ground control points (GCP). This model comes at the issue from a different angle. Instead of constructing a physical model defining the sources of distortion, its direction and magnitude this other model uses empirical methods that compare differences between positions of known points on both remote sensing images and maps of suitable scale (Mather, 2005).

3.3.2.3 Atmospheric correction

Atmosphere can have a significant effect on the level of reflection from features on the surface through scattering and absorption (Jensen, 2005). The effect of this on the DN of remote sensing images is that scattering tends to increase their values while absorption reduces them. The extent to which atmosphere affects the DN can be best seen in a histogram of the spectral values (Gibson & Power, 2000).

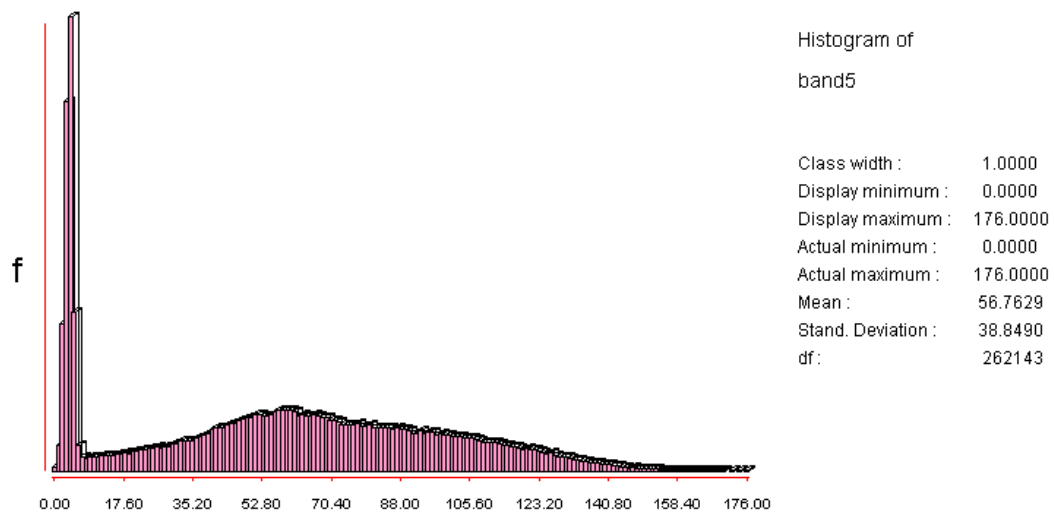


Figure 3.3 Example of a histogram of data from band 5 of Landsat 5 thematic mapper (Sr.Nicholas M. Short, 1997).

Atmospheric correction is most often needed when the sensor data parameter being looked at is biological in nature. An example of that kind of analysis is extracting NDVI data from Landsat Thematic Mapper (TM) data to measure biomass and plant health. Atmospheric scattering could increase the NDVI values in areas of broken or scattered vegetation, drastically altering the results (Jensen, 2005).

There are two types of atmospheric correction: absolute and relative correction. Absolute correction involves turning the DN values into scaled surface reflectance values which can be compared with scaled surface reflectance obtained from anywhere else on Earth. Absolute correction can be further divided into physically-based and imaged-based methods. Physical-based methods require *in situ* data taken in the field of the light and atmospheric conditions at the time the image is recorded. Invariant object methods are an example of physically-

based atmospheric correction. Algorithms using this method work on the assumption that in any given image there are some pixels that have reflectances that are relatively stable. These pixels are known as invariant objects and a linear relationship can be made with each spectral band based on the reflectance of the invariant objects, which can then be used to normalise images acquired at different times (Liang, Fang, & Chen, 2001). Image-based methods use measurements of certain objects of known brightness recorded by multispectral imagery. The multispectral sensor observes the effect of scattering or absorption on the bands being measured, which is then compared with the object of known brightness revealing the values attributed to the effect of the atmospheric distortion.

An example of an image-based atmospheric correction technique is dark object subtraction (DOS). This is used as both a radiometric and an atmospheric correction method. Its purpose is to reduce the effect of scattering by the atmosphere, ensuring that certain spectral signatures are not over- or under-represented in the data (Chavez Jr, 1988). In this method it is assumed that any radiation received by the sensor from dark objects is from atmospheric path radiance. This refers to the radiance received by the sensor that is not from the object or feature under observation but has been produced by atmospheric scattering. The process of DOS selects all the lowest DN values, often from specific features in the image such as water bodies. These values are then subtracted from all the pixels across the whole image. Though this method is effective it is not capable of compensating for atmospheric transmittance (Chen, Vierling, & Deering, 2005).

Relative correction takes a different approach by selecting ground targets called “PIF” with near constant spectral values over time and having a range of brightness. They also need to have a similar elevation, be relatively flat, and only have minimal amounts of vegetation. These points are then related to the image used for study (Jensen, 2005).

3.3.2.4 Radiometric correction

Analogue and digital remote sensing images produced by remote sensing devices can contain errors known as radiometric distortions, which are introduced by the sensing system (Gibson & Power, 2000). These errors are related to the unique radiometric resolution of different remote sensing platforms. Radiometric resolution is related to how finely a remote sensing system can represent differences in intensity within an image. A digital image is normally represented in divisions called bits; it can have up to 8 or 12 bits, and also 256 or 4096 levels of grey. This is known as digital numbers data: a compressed form of data used to transmit information from satellites to Earth (Lillesand et al., 2008). If a researcher were to use data from two different satellites, errors would occur in the analysis due to the different DN data produced by each satellite (Lillesand et al., 2008). The other factor that causes radiometric distortions is the time difference between remote sensing images. The incident angle of the sun in relation to the target object and the remote sensing platform changes over time.

The algorithms to correct radiometric distortions can be absolute or relative, as mentioned in section 3.3.2.3. Regardless of the algorithm used, the radiometric correction normally follows a two-step process that goes as follows. Firstly the DN data from the sensor is converted to spectral radiance, which is a measure of how much radiation is emitted or passes through an object. This is necessary as DN values, though usefully do not present brightness in physical units (Campbell & Wynne, 2011). An example of the formula used to perform this process is:

$$L_{sat} = DN * Gain + Offset$$

Where:

L_{sat} = The spectral radiance detected by the satellite

DN = the digital numbers of the sensors measurements

Gain + Offset are the sensor-specific calibration settings determined before the sensor is launched.

Equation 3.3: DN to radiance conversion example (Chen et al., 2005)

The next step is to convert the radiance to surface reflectance. An example of an equation to perform that process (Chen et al., 2005) is:

$$P_{\text{surface}} = (L_{\text{sat}} - L_{\text{path}}) \cdot \rho_t / E_t$$

Where:

P_{surface} = this is the ground surface reflectance of the target feature

L_{path} = the path radiance

E_t = the irradiance of the ground target

ρ_t = the transmission of the atmosphere

Equation 3.4: Conversion from radiance to reflection example (Chen et al., 2005)

It is necessary to convert to reflectance because DN and radiance as measures of brightness are subject to change by differences in sun angles, atmospheric effects and angle of observation of the sensor. Reflectance is much more useful as it is a measurement of the amount of radiation reflected from a variety of objects relative to the wavelengths incident upon the feature of interest. Ground level reflectance measurements are usually not achieved in remote sensing as it requires *in situ* data of the wavelengths, angles of illumination and atmospheric conditions at the time of the remote sensing observation. This method is not always practical on a regular basis and so an estimation of top of atmosphere reflectance is made using an equation like this (Campbell & Wynne, 2011):

$$Q_Q = (P_i \cdot L_{\lambda} \cdot d^2) / (E_{\text{SUN}} \cdot \cos \theta_s)$$

Where:

Q_Q = at sensor in band reflectance

L_{λ} = at sensor in band radiance

E_{SUN} = mean solar exoatmospheric irradiance

θ_s = is the solar zenith angle

d = is the Earth sun distance in astronomical units.

Equation 3.5: Example of a top of atmosphere reflectance conversion

The parameters of this equation can all be sourced from databases that have records of the information required for solar zenith angle and Earth sun distance for any time and day of the year. The rest of the information is derived from the meta data of the remote sensing images (Campbell & Wynne, 2011).

3.3.3 Image enhancement

The spectral bands of an image can be arranged in a variety of different combinations creating a colour composite image (Jensen, 2005). This type of analysis is described as spectral analysis. These images can be presented using both true and false colours. Depending on the object that the analyst wants to detect, different band combinations can be used for specific types of features. True colour images use red, blue and green light (Gibson & Power, 2000). This could be useful if an analyst wanted to identify vegetation within an image. If non-visual bands were combined then the image would be a false colour composite that may highlight vegetation within the image, making classification of vegetation and non-vegetation land-covers easier (Lillesand et al., 2008).

Not only can the spectral bands be put together in composites to highlight certain features, they can also be manipulated to perform spectral-based analysis. One example of such analysis used to look specifically at vegetation is the normalised difference vegetation index or NDVI (University of Reading, 2002). This provides a measure of vegetation biomass. It is similar to band ratios using infrared and red light. Band ratios are images formed by dividing the DN of one band by the corresponding DN of another band. This technique enhances the gradient changes in spectral reflectivity between surfaces (Jensen, 2005). The NDVI differs from band ratios in that it does not use DN but looks at the wavelength ranges between near infrared (NIR) and red light (R). It takes values between -1 and 1, with 0 being no vegetation and 0.5 indicating dense vegetation (University of Reading, 2002). The limitations of NDVI images are that they can be affected by the amount of incident radiation from the sun and the radiometric response of the satellite as well as atmospheric characteristics (Lillesand et al., 2008). However, most of these problems can be taken care of with an image correction process, which will be discussed later in the chapter.

$$\text{NDVI} = (\text{NIR} - \text{R}) / (\text{NIR} + \text{R})$$

Where:

NIR = near infrared

R = red

Equation 3.6: Normalised difference vegetation index (NDVI) using near infrared and red wavelengths

3.4 Classification systems

Being able to categorise and conceptualise different land-covers is essential to monitoring and understanding changes occurring to the environment (Gregorio & Jansen, 2000). Geographic concepts such as “roads, forests, rivers” may not always be represented in the same way depending on the perspective of the group portraying those concepts. When classifying land-cover the importance of using a consistent land-cover system throughout all of the research cannot be understated (Kavouras & Kokla, 2008). Any inconsistencies can undermine any research relating to interpreting changes and interactions related to land-cover (Gregorio, 2005). Differences in the taxonomy of geographic features depend on methodology, the discipline of the researcher, culture and scale (Kavouras & Kokla, 2008).

There have been a number of land-cover and land use classification schemes that have been developed to interpret remote sensing data. Each was developed for a specific application. Some examples of these are the American Planning Association’s Land-Based Classification Standard (LBCS). The LBCS scheme requires high resolution satellite images, *in situ* surveys and aerial photography, as it focuses on land use that requires a high degree of detail in the data. Another example is the United States Geological Survey’s land-use/land cover classification system, which is designed for use with remote sensing data (Anderson et al., 1976). This system’s main focus is land-cover classification for the purpose of managing resources (Jensen, 2005). Another scheme, produced by the Food and Agriculture Organization of the United Nations (FAO) and called Land Cover Classification System (LCCS), is similar to Anderson’s system. It focuses on land-cover and is designed to be used with remote sensing data (Food and Agriculture Organisation of the United Nations (FAO), 2012). It is a unique system that combines the benefits of a standardised set of classes while still providing the flexibility to use the system on any land-cover anywhere in the world. Most land-cover systems are single use and need to generate a large number of pre-defined land classes to use for any analysis. However instead of finding a classification system with the right number of pre-defined classes for a particular location, the LCCS defines the criteria to determine the type of classes used in the classification (Food and Agriculture Organisation of the United Nations (FAO), 2012).

Classification systems in general are hierarchal and flexible enough to be able to classify features at different scales (Commison, 2001). They are designed this way because of the variety of different data they can work with. Based on the literature, the US Geological Survey's land-use/land-cover classification system has become widely adopted and also forms the basis of other classification systems (Florida State Government, 1999; Foreman, Pickett, & Zipperer, 1997; Mubea, Ngigi, & Mundia, 2011; Rossiter, 1994). The reason this system is so widely used is that it has been designed to interpret remote sensing imagery in a variety of resolutions and scales by having four levels of classification (see Table 3.1) (Jensen, 2005).

Table 3.1: Types of remote sensor data used for the USGS Land-Use Classification System for Use with Remote Sensor Data (Jensen, 2005).

Classification level	Typical data characteristics
I	Satellite imagery such as NOAA AVHRR (1.1KM), MODIS (250m; 500m) Landsat MSS (79m), Landsat TM (30 x 30m), and SPOT XS (20 x 20m)
II	Satellite imagery such as SPOT HRV multispectral (10 x 10 m) and Indian IRS 1-C panchromatic (5 x 5 m) High-altitude photography acquired at scales 1:20,000 to 1:80,000
III	Satellite imagery with 1 m to 2.5 m nominal spatial resolution Medium-altitude aerial photography at scales from 1:20,000 to 1:80,000
IV	Satellite imagery with = <1 m nominal spatial resolution (e.g. QuickBird, IKONOS) Low-altitude aerial photography at scales from 1:4,000 to 1:20,000

Levels I and II are best suited for classifying features at a national level, whereas levels III and IV are more designed for a regional or local scale. However, the levels are not designed to restrict users to specific data sets as it is possible to classify images from Landsat data using both levels I and II. The last two levels are generally left for the user to customise because of the need for increased flexibility at smaller scales (see Table 3.2) (Anderson, Hardy, Roach, & Witmer, 1976).

Table 3.2: Example of different land-cover classes at levels I and II of the USGS Land Use Classification System for Use with Remote Sensor Data (Jensen, 2005)

Classification level I	Classification level II
Water	Open water Perennial ice/snow
Developed	Low-intensity residential High-intensity residential Commercial/industry/transportation
Barren	Bare rock/sand/clay Quarries/strip mines/ gravel pits Transitional
Forested Upland	Deciduous forest Evergreen forest Mixed forest
Shrub-land	Shrub-land
Non-Natural Woody	Orchards/vineyards, other
Herbaceous Upland Natural/Semi-natural Vegetation	Grasslands/herbaceous
Herbaceous Planted/Cultivated	Pasture/hay Row crops Small grains Fallow Urban/recreation Grasses
Wetland	Woody wetlands Emergent herbaceous wetlands

3.4.1 Digital image classification

Image classification is a process that involves assigning pixels to various classes. Each pixel gets an individual unit that is composed of several bands. This allows the pixels to be grouped by comparing unknown classified pixels with pixels of known identity using reference data. There are many types of land classification , but for the application of change detection, land-cover and land use classification are most frequently adopted (Campbell & Wynne, 2011). Land-cover refers to what features are present on the Earth's surface; for example, lakes, forests and highways. Land use is related to what human activity or economic function a specific piece of land has (Lillesand et al., 2008).

Land use classifications are scale dependant. An example of this could be a map of a city's urban area. At a lower scale it would be classed as residential and commercial. It is even possible to divide a residential area further into single-family dwellings (Lillesand et al., 2008). These classes could be mistaken for land-cover; however it is the context in which they are used in terms of describing human activity on the land that distinguishes them as land uses. There are many methods of classification. The most widely used are unsupervised, supervised and hybrid classification (a combination of the first two methods) (Lillesand et al., 2008).

3.4.1.1 Unsupervised classification

This technique involves clustering the pixels based on the distribution of the digital numbers within the image. It is a relatively automated process but, depending on the classification program being used, the analyst would normally have to input values such as the maximum number of classes, maximum iterations and a threshold value (Gibson & Power, 2000). Unsupervised classification techniques are designed to identify the natural groupings (representing spectral signatures) that occur within multi-spectral remote sensing data. The process to identify these natural groupings in the data can be illustrated using a scatter plot with two axes representing different spectral bands. The actual process in reality occurs in "N-dimensional" data space with many spectral bands being analysed for patterns (Campbell & Wynne, 2011).

The basic principle of how the method works is that the computer picks out spectral values within an image that have similar spectral signatures and assigns unknown classes to each group of pixels. The analyst then uses reference data to reclassify the unknown classes (Jensen, 2005).

A number of techniques are used for unsupervised classification. The two main methods are k-means and isodata. K-means is an algorithm that puts the groups of spectral signatures into bivariate normal distributions. It is assumed that that the data in k-means has a number of known clusters but the centres are unknown. In the first iteration, points are added that are the best guess of where the centre of each cluster is. Then, using the shortest distance to centre rule, new points are placed that are the shortest distance between the first point and the

cluster's centre. The values of the cluster are then averaged; the process is repeated and continues until there is no difference between the projected points and the centre of each cluster (Mather, 2004). Isodata, unlike k-means, does not assume that there are a known number of point clusters. Isodata instead assumes that there is an indeterminate number of clusters that are tightly grouped around their centres. The other assumption is that each cluster is separated beyond a user-specified threshold value. Once all of the first clusters are established the iterations begin. After every iteration, the standard deviation of the values in each cluster is calculated. The clusters that have large standard deviations beyond the threshold are further divided until all the clusters are within the threshold (Mather, 2004).

Unsupervised classification provides an analyst with the ability to get a detailed image of all the various spectral signatures with in an image. This is particularly important if there is spectral confusion between certain classes. For example, barren land and built-up land often show up under the same class. One example of unsupervised classification has been used in a land-cover classification was a study done in west Bengal, which covers 8686.63 ha and lies on the east coast of India, including peaks in the north of the Himalayas and coastal plains in the south-east. The purpose of the study was to monitor changing farm practices using remote sensing and geographic information systems. The satellites used were the AwiFS, which has a spatial resolution of 56 m, and the WiFS, which has a spatial resolution of 188 m. A combination of methods was used in the classification of a series of multi-date images. For the non-agricultural areas a k-means algorithm was used with NDVI as the input data. The crop classification was performed using an isodata algorithm with further refinement of the classes achieved with supervised classification (Manjunath, Kundu, Ray, Panigrahy, & Parihar, 2011). This shows how for a particular application, such as determining the location of particular classes (urban areas) and also creating a base classification, unsupervised classification is relatively well suited to show the natural structure of the data revealing all of the different spectral signatures within the image.

3.4.1.2 Supervised classification

Supervised classification relies greatly on user inputs before a processing algorithm is chosen, unlike many of the unsupervised classification methods, which require very little user input. The inputs for supervised classification can be sourced from field work, aerial photographs or maps of a study area (Mather, 2004). Supervised classification can be defined as a process of taking samples of pixels of known identity to classify pixels of unknown identity. Factors to consider in this process include:

- samples should exemplify the spectral signatures of the categories they represent
- sample training areas should not straddle land-cover boundaries. The size, shape and position of the sample training areas should try to favour convenient identification both on the remote sensing image and in the field (Campbell & Wynne, 2011).

There are three basic steps to any supervised classification:

- 1 the training stage, which involves the analyst taking samples of the image to develop numerical descriptions of each land-cover, based on their spectral signatures
- 2 the classification stage, where the analyst assigns a classification to each sample or training class, using various reference data sets and a classification scheme. This sample data set is then compared with the pixels of the image and each individual pixel is given a class. Those pixels that do not fit inside any of the classes are labelled as “unknown”.
- 3 the output stage, where a map of the different classes is generated (Lillesand et al., 2008).

Though supervised classification in general does follow the three steps as outline above, there are a variety of methods that can be used. These include parallelepiped classification, minimum distance to mean, isodata and maximum likelihood (Campbell & Wynne, 2011).

- **Parallelepiped classification:** This creates boxes representing the range of values within the training samples, to which all unassigned pixels are then assigned.
- **Minimum distance to mean:** This is similar to k-means except the data clusters used in it are created by the user. Values outside the clusters are assigned to the mean of each cluster using the minimum distance to centre rule.
- **Isodata:** This is similar to the minimum distance to mean rule. The difference is that, at end of every iteration, the algorithm for the mean of each cluster is re-calculated.
- **Maximum likelihood:** This is the only one the four methods that addresses the issue of variation within each of the spectral classes. Some pixels within an image will likely be represented in more than one class, which means that the first three methods may have certain classes either under- or over-represented. Maximum likelihood classification is based on the probability that pixels will be in one class or another and choosing to put each pixel in the category that will ensure the highest likelihood of a correct classification (Campbell & Wynne, 2011). It is the ability of maximum likelihood to assign pixels to classes when more the one spectral signature is present within the cell that makes it one of the most accurate methods for supervised classification. Based on the literature it is also a widely used method (Ahmad, 2012; Akgun, Eronat, Turk, & Eylul, 2004; Devi & Baboo, 2011)

3.4.1.3 Advantages and disadvantages of unsupervised and supervised classification

Each of these techniques has specific ways in which it can be best applied. However both of these methods have limitations that create difficulties for analyst. Firstly, unsupervised classification has three advantages over supervised classification.

- 1 Analysts do not require extensive knowledge of the study area. The opposite is the case with supervised classification, where training samples are based on reference data about the study area. Because there is less human

involvement in unsupervised classification there are also fewer chances for human error as well.

- 2 The categorisation of spectral classes is based on the natural structure of the data. This is important, as unique spectral signatures that are often missed in supervised classification are revealed with unsupervised methods. Unfortunately, unsupervised classification is so good at picking out every little detail in an image it can make it difficult to reclassify the results into the information classes used in the classification scheme. The lack of control over the process means that an analyst has less control over the selection of classes and their identity.
- 3 The spectral properties of some information classes change over time because of the relationship between informational classes and spectral classes. These relationships are not constant, which means once the relationship is defined for one image it cannot be extended to another (Gibson & Power, 2000).

Although unsupervised classification gives an analyst more flexibility in their analysis, sometimes it is necessary to tailor the information categories specifically to the needs of the study area. In supervised classification it is possible to make a more specialised classification because of the reference data an analyst uses to generate the training samples. There is also the benefit of not having to deal with the issue of matching unassigned spectral categories to the information classes, as this is done during the creation of the training samples. The training samples also help the analyst to detect errors; they act as a reference to accuracy so that, when checking the final map, the polygons representing the training samples can show where areas have been wrongly classified.

The control that supervised classification provides over the data, though useful in some cases, does create the potential for errors where the structure dictated by the user does not match the natural structure of the data (Gibson & Power, 2000).

3.4.2 Hybrid classification

Hybrid classification aims to combine the strengths of both unsupervised and supervised classification, and a variety of methods have been developed to

achieve this goal (Lillesand et al., 2008). One frequently used method is guided clustering. This was used as part of a study in 1994 in Minnesota investigating alternative methods of classification that could be integrated into the state's departmental natural resource forest management strategy (Bauer et al., 1994). Guided clustering is a six-step process that uses the isodata, unsupervised classification and maximum likelihood supervised classification algorithms.

- 1 Display the training areas for the different classes within the image. These are unsupervised training areas that, unlike supervised training areas, do not have homogenous spectral signatures (Lillesand et al., 2008).
- 2 Use the isodata method to cluster training class (x) into spectral subclasses.
- 3 Examine the subclasses and remove or merge the various classes as needed.
- 4 Repeat steps 1 and 2 for all of the other training classes.
- 5 Perform the maximum likelihood classification using all of the spectral subclasses.
- 6 Generalise the image using techniques such as majority filtering (Bauer et al., 1994).

Another example of hybrid classification was conducted by Pradhan 2010 in Sikkim, India, looking at general land-cover change (Pradhan, Ghose, & Jeyaram, 2010). This method used the k-means algorithm for the unsupervised classification and the Bayesian method for the supervised classification. The Bayesian algorithm is similar to maximum likelihood as it uses probabilities to assign land-cover classes. The first step when using this technique is to use the k-means to refine the training patterns of the various spectral classes. The training patterns are then processed by the Bayesian classifier. It was found that when using the Bayesian classifier alone the accuracy was 90.53 per cent but the hybrid method yielded an accuracy of 91.59 per cent, indicating a slight improvement in the certainty of the classification. Part of this high accuracy may have been attributed to the training sample being used as ground truth information instead of actual data (Pradhan et al., 2010).

3.4.3 Other methods of classification

3.4.3.1 Fuzzy classification

Geographic features in the real world generally do not have discrete boundaries. Objects or phenomena in a landscape that are classified have heterogeneity within the classes, for example types of forest may have differences within them that are due to age, species or health. Most other classifications use the classical set theory that allocates precisely defined values to pixels of an image, making each pixel either a member of a particular class or not. Fuzzy set theory on the other hand does not use well-defined boundaries, which means that any pixel may have partial membership of a number of classes (Jensen, 2005). Fuzzy classification uses a similar training technique as used in supervised classification but, instead of assigning pixels to a single class, it is possible to assign values to pixels that reflect the transition from one area with complete membership of its classes to another. To achieve this using training set data extracted from a satellite image requires selecting training samples that consist of both pure and mixed land-covers.

To illustrate how this might work, imagine there is a transition of pixels going from water to forested wetland. Pixel values less than 24 have membership grades of 1 for water and values greater than 70 could have a membership grade of 1 for forest wetland. This means that all the values between 24 and 70 would be on a gradient of membership grades between 0 and 1. Therefore a pixel with a value of 30 would have membership grades of 0.5 for water and 0.5 for forested wetland (Jensen, 2005). An example of an application of this method was a study done in 2006 where historical aerial photographs were classified and validated using the fuzzy c-means algorithm. This algorithm assigns pixels to each land-cover class in proportion to the area of each pixel that the various classes cover. Fuzzy c-means has a number of variations that allows it to be used as both an unsupervised or supervised method. The purpose of the study was to exhibit how fuzzy classification can be used to create an error matrix (a table used to measure the accuracy of classifications) to validate classifications in situations where ground truth data is either unreliable or cannot be obtained. Fuzzy classifications can be used to create error matrices by taking the first fuzzy classification and reclassifying the values so that each pixel is classified with the class it is most

likely to occupy. It is then compared with the original fuzzy classification which is used as the reference data. The method is based on the assumption that the first fuzzy classification is an accurate representation of the true ground cover (Okeke & Karnieli, 2006).

3.4.3.2 Object-oriented image segmentation

Remote sensing systems such as IKONOS and GeoEye produce images of such high spatial resolution that the normal pixel-based classification algorithms cannot get the required detail to distinguish certain features from each other. For example, in urban areas the complexity of the spectral signatures of things such as roads, roofs, vegetation, soil and water makes it very hard to differentiate between different features. Another issue is that the data being displayed in each individual pixel is actually influenced by the area surrounding it. These two problems prompted the creation of classification algorithms based on the object orientated image segmentation (Jensen, 2005). This is a two-step process that mimics the logic that human interpreters use to identify different sizes, shapes and textures as well as spectral characteristics used for conventional pixel-based classification.

The first step is segmentation of pixels into objects (Campbell & Wynne, 2011). This involves the identification of the edges of patches of homogeneous land-cover. The creation of the objects is a hierarchical process that works on a number of scales that nest within each other. Each region is based on its spectral values and a user-specified threshold. Once an image is segmented into objects, it is classified using a conventional classification method such as nearest-neighbour or fuzzy classification. The objects are characterised by the various properties that are developed as a result of the segmentation process, which is used to assign the classifications (Campbell & Wynne, 2011). The usefulness of this technique was demonstrated in a study done in 2006, which used both object-based and pixel-based classification methods to overcome topographic distortions (Gholoobi, Tayyebi, Taleyi, & Tayyebi, 2010). They used a unique segmentation algorithm called eCognition, which was developed in 1999. ECognition is a multi-resolution, bottom-up method that starts with pixel-sized objects and expands to much larger ones after several iterations (Baatz & Schape, 2000).

3.5 Accuracy assessment

Remote sensing data is becoming progressively more important for environmental modelling. However, models using this information have to deal with the inherent error that is present in all remote sensing data. That is why it is vitally important for the results of any remote sensing analysis, that an accuracy assessment be performed so analysts have a measure of uncertainty for their work (Jensen, 2005).

One of the most commonly used methods for accuracy assessment is the error matrix. Some papers that have been recently published indicate that the method may have some limitations when being used to test more complex classifications (Congalton & Green, 2009). However it is still a widely adopted method used to test a great variety of classifications (Congalton, 1991; Foody, 2001; Zăvoianu, Caramizoiu, & D.Badea, 2001).

3.5.1 Classification of error matrices

The error matrix – also known as a confusion matrix – refers to the way the in which a matrix can illustrate not only the overall errors in each classification category, but also all misclassifications that have occurred (Campbell & Wynne, 2011). An error matrix is a site-specific accuracy measure that is based on the agreement of the map and reference data at specific locations, whereas non-site-specific accuracy assessment refers to a comparison of two images based on the total areas of each class (Campbell & Wynne, 2011). An error matrix considers the relationship between reference data and the result of the classification. These matrices are square with an equal number of columns and rows for each of the categories (Lillesand et al., 2008). It provides a user with a description of the classification, which can help refine further classifications as well as any conclusions made from the first classification (Jensen, 2005). An example of a typical error matrix can be seen in Table 3.3. The columns represent the ground reference data and the rows represent the classification data produced from a remote sensing image. Where the rows and columns intersect depicts the number of sample units assigned to each corresponding class. In this example the total number of samples is symbolised by “N”. Within the matrix the symbols in the diagonal cells equate to those pixels or polygons that were appointed to the

correct class. The non-diagonal cells, however, stand for errors in the classification. These errors come in two forms. They are either a commission error, which is an error of inclusion, or an omission error, which is an error of exclusion.

Table 3.3: Example of an error matrix (Jensen, 2005)

Ground reference test information						
	Class	1	2	3	k	Row total
Remote sensing classification	1	X _{1,1}	X _{1,2}	X _{1,3}	X _{1,k}	X ₁₊
	2	X _{2,1}	X _{2,2}	X _{2,3}	X _{2,k}	X ₂₊
	3	X _{3,1}	X _{3,2}	X _{3,3}	X _{3,k}	X ₃₊
	k	X _{k,1}	X _{k,2}	X _{k,3}	X _{k,k}	X _{k+}
	Column total	X ₊₁	X ₊₂	X ₊₃	X _{+k}	N

3.5.2 Important considerations when constructing an error matrix

When constructing an error matrix the analyst must compare two sample data sets: a reference data set and a data set produced from a classified image. Each sample data set is produced by extracting data from both the reference data and the remote sensing data using either points or polygons. It is also important that each sample location is randomly placed to ensure there is no bias. Errors in the creation of the sample data set can lead to errors in the classification (Campbell & Wynne, 2011).

Landscapes constantly change, so it is crucial to obtain reference data around the same time as the most recent remote sensing image. Ideally this would involve actually visiting the study site and going to the locations of the random sample sites. However some sites may have restricted access due to terrain or climate, or because they are on private or government land that may be off limits. The solution in this case is to use images higher in spatial resolution data such as Google Earth, images from satellites like QuickBird or GeoEye as well as aerial photography (Jensen, 2005). When analysts are looking at random sample locations in the sample data sets, they usually do not look just at the pixel in each location, but instead take note of the pixels surrounding the central pixel. The sample site is then assigned the land-cover that is the highest in frequency at that

location. This practise minimises the effects of geometric mis-registration of a land-cover in the classified data (Jensen, 2005).

The sample size is also an important factor to consider. As a general guideline, a minimum of 50 samples of the various classes should make up an error matrix. More samples are appropriate if the study site is relatively large or if there is a great number of classes. Sample numbers should also be modified based on the relative importance of a certain category, as well as the frequency that a particular class occurs within the data (Lillesand et al., 2008).

The type of sampling scheme has a major influence on the make-up of an error matrix. Three schemes are considered here: random sampling, stratified sampling and systematic sampling.

- **Random sampling:** This technique involves dividing the study area into a grid with each column and row numbered. A random number generator selects numbers from the rows and columns in pairs that represent coordinates of the sample locations. The benefit of this technique is that every location within the grid has an equal chance of being selected. However some classes can be under-represented if they occur less throughout the image, as the distribution of the sample sites is not always equal (Campbell & Wynne, 2011).
- **Stratified sampling:** This technique assigns sample locations to sub-regions of a study area. This insures that every category is sampled. The technique can also be combined with random sampling to reduce bias as well as making sure there is an equal distribution of sample sites (Campbell & Wynne, 2011).
- **Systematic sampling:** This method is completely different from the other two. Systematic sampling works by placing sample sites at equal intervals using a specific strategy. This method has the benefit of creating an equal distribution of sample sites as well as an equal representation of each category. However because the placing of the first site predetermines the locations of all the other observations the process cannot be randomised, this can lead to misrepresentation of some errors within the error matrix (Campbell & Wynne, 2011).

3.5.3 Evaluation of error matrices

The evaluation of an error matrix is done by conducting statistical analysis using descriptive statistics and multivariate techniques. The descriptive statistics include: producer's accuracy, user's accuracy and overall accuracy. Producer's accuracy is a measure of omission error. It is created by dividing the values in the diagonal cells (that represent the correct classifications) with the row total. Producer's accuracy is so named because an analyst is interested in how well certain areas can be classified. User's accuracy is very similar, but instead of the correct classifications being divided by the row total it is the column total. User's accuracy is a reliability figure that indicates the probability that a pixel on a map actually represents the same class on the ground. Overall accuracy is calculated by the sum of all correct classifications divided by the grand total (Lillesand et al., 2008).

An example multivariate technique that could be used is the kappa statistic, shown in Equation 3.7. It uses a formula called the Khat coefficient of agreement, which produces an estimate of the kappa statistic. Kappa can be defined as a measure of the agreement between the remote sensing-derived data and the reference data indicated by the values in the diagonal cells of the matrix as well as the chance agreement indicated by the row and column totals. Kappa values that are greater than 80 per cent are considered to have strong agreement between the classification map and the reference data. Values that are below 40 per cent are said to have very poor agreement; anything in between is seen as moderate accuracy (Jensen, 2005).

$$\kappa = \frac{(N \sum_k X_{kk} - \sum_k (X_{k+} X_{+k}))}{(N^2 - \sum_k (X_{k+} X_{+k}))}$$

Where:

k = number of rows in the matrix

X_{kk} = the number of observations in row k and column k

X_{k+} and X_{+k} = are the marginal totals of row k and column k

N = is the total number of observations

Equation 3.7: Kappa statistic calculated by the Khat coefficient (Jensen, 2005)

3.6 Land-cover change detection using GIS

Observing multiple images from the same location over time allows analysts to measure changes in the type or condition of features on the surface. This is known as change detection (Campbell & Wynne, 2011). The changes this technique measures can be on multiple spatial and temporal scales, and can be the result of both natural and human influences on the landscape. Examples of the range of applications of change detection include looking for changes in snow cover, change in flood waters, urban fringed development or desertification (Lillesand et al., 2008).

Land-cover changes can be put into two categories: land-cover conversion and modification. Conversion of land is the complete replacement of one type of land-cover to another; for example, deforestation and agricultural expansion. Land-cover modifications have a more subtle effect on the land as they alter small parts of a landscape without changing the whole classification of any land-cover (Lambin, Geist, & Lepers, 2003). Land-cover modification has in recent years had more recognition in terms of its importance regarding how such changes affect people and the environment. One example of this is the increase in food production during the 1990s thanks to high-yield crop varieties, fertilisers, irrigation and pesticides (Lambin et al., 2003) .

Land-cover change detection techniques can be put into two categories: pre-classification and post-classification.

3.6.1 Pre-classification change detection

Pre-classification change detection produces “change” “no change” information from a single analysis of a combined data set of multiple images for two or multiple dates. It is a method that uses pixel-wise operations and has a number of different techniques, including visual interpretation of composite images and image differencing as well as principle components. The advantage of pre-classification is that it does not rely on a classification that will always have a certain degree of error and so those errors in classification do not affect the change detection analysis. However the weakness of the pre-classification approach is that it cannot give detail on how certain changes occur because, without land-cover classification incorporated into the analysis, changes between land-covers cannot be seen. An example for pre-classification change detection research was conducted for the Uttarakhand district in India, which is in the middle Himalayas. The purpose of the study was to track the forest cover change from 1976 to 2006. The pre-classification method used was visual interpretation of composite images. The analyst produced vector maps indicating areas of change for both 1976 and 2006 comparing the changes in a table to quantify the amount of change (Munsi, Malaviya, Oinam, & Joshi, 2010).

3.6.2 Post-classification change detection

Post-classification change detection involves comparing the changes from one class in the first image to another class in the second image, producing “to” “from” change information about both independent classifications. This gives the user some idea of how the different elements of the landscape are interacting to cause the change. The problem with post-classification change detection is that it is reliant on the accuracy of the independent classifications to make correct conclusions with the analysis.

An example of this technique in use can be seen in a paper on land-cover change in the Karnataka of India in the Himalayas. Using Landsat data from 1986 and 2003 the researchers used a combination of pre- and post-classification methods (Virk & King, 2006).

The pre-classification techniques were image differencing and principle components. Image differencing involves taking two images from different times and subtracting the DN of one from the other. The output from this process is an image with values that show the difference between the two time periods. Any value close to zero represents no change. The analyst sets a threshold value that indicates when change has occurred, which is then seen in the output image (Lillesand et al., 2008). The principle components method combines two images into a multi-band image containing all the bands from both images. Where the principle components of both images do not correlate with each other in the new image, this indicates change (Lillesand et al., 2008). The image differencing was performed on an NDVI image and the principle components was performed on a greenness index image showing the amount of greenness from vegetation detected in the infrared and red bands.

The post-classification change analysis was performed by creating a deforestation/reforestation map, which compared a forest change classification map with the NDVI images that had the best results out of the pre-classification change methods. The results indicated that most of the deforestation was caused by forest being submerged due to hydroelectric developments. Reforestation was seen to increase due to community forest planting projects (Virk & King, 2006).

Whatever type of change detection is conducted, the analyst has a number of things to consider before any change detection is done. Firstly the images being used must be as similar to each other as possible, in terms of the type of sensors being used; they must cover exactly the same area and they should be taken around the same time of day and year. Researches also need to look for images with ideal conditions that have clear weather and no elements within the image that interfere with the detection of the feature of interest. Also it is essential that atmospheric correction processes are conducted (Campbell & Wynne, 2011).

Chapter 4: Paper

Investigating the impact of tourism on forest cover in the Annapurna Conservation Area through remote sensing and statistical analysis

This chapter has been prepared as a stand-alone paper submitted to the *Journal of Applied Geography* for peer review. There have been some formatting changes due to the requirements the Journal as well as some repetition with respect to the abstract as well as the introduction, discussion and conclusion chapters.

Abstract

Tourism is Nepal's largest industry, giving people in rural areas an alternative to subsistence farming. Tourism can have an impact on the forest cover of a region as trees provide firewood for cooking and heating and timber for building accommodation. In 1986 the Annapurna Conservation Area Project was established to ensure that tourism was managed sustainably, which includes minimising its impact on the forest cover. This study assesses the impacts of tourism on the forest cover in the Annapurna region by comparing Landsat images from 1999 and 2011. This was achieved through spectral classification of different land cover and assessing the change in forest cover in relation to increasing distances from tourism villages. A major problem with remote sensing in mountainous regions such as Nepal is shadow caused by the relief. This issue was addressed by only assessing areas which were free from shadow, which in effect meant a sample was used rather than the whole study region. The results

indicate that there has been an 8 per cent reduction in overall forest extent, but this change varies by region. In the northern, drier regions there has been a net increase in forest cover, while in the southern regions there has been a net reduction in forests. The influence of tourism facilities on forest is also variable. Around each of the sample tourism villages there was a general trend of forest removal, decreasing as the distance from each village increased, which indicates tourism does have a negative impact on forests. However, there was an opposite trend in the northern villages that were well inside the conservation area.

Key words: Nepal, Annapurna, remote sensing, tourism, forest cover

Introduction

Over the past 30 years, Nepal's tourism industry has experienced rapid growth, apart from a period from the mid-1990s to 2006 when there was a conflict between the Maoists and the government. The main interest for tourists is the "Tea House" trekking in the Everest and Annapurna regions, which are world renowned for including close views of the highest mountains in the world, and are provisioned with numerous lodges and restaurants. This study focuses on the Annapurna Conservation Area (ACA), which consists of 7683 km² and has a population of approximately 100,000 people spread between 300 villages (Mayhew & Bindloss, 2009).

Figure 1 shows the location of the ACA, and shows the popular trekking routes which have made this region famous. The main attraction for trekkers is the Annapurna circuit. The Annapurna circuit is around 300 km in length and takes approximately three weeks to trek (Mayhew & Bindloss, 2009). It covers a variety of land-cover types, including temperate and tropical broadleaf forests in the southern parts, which are lower in elevation and generally wet. In the more central northern section, the land cover consists of conifer forest and alpine deserts and is high in elevation and generally dry (Shrestha, 2001). With lodges and tea houses spread along the circuits, trekkers can carry minimal supplies and have accommodation and food available to purchase during the entire journey (Mayhew & Bindloss, 2009).

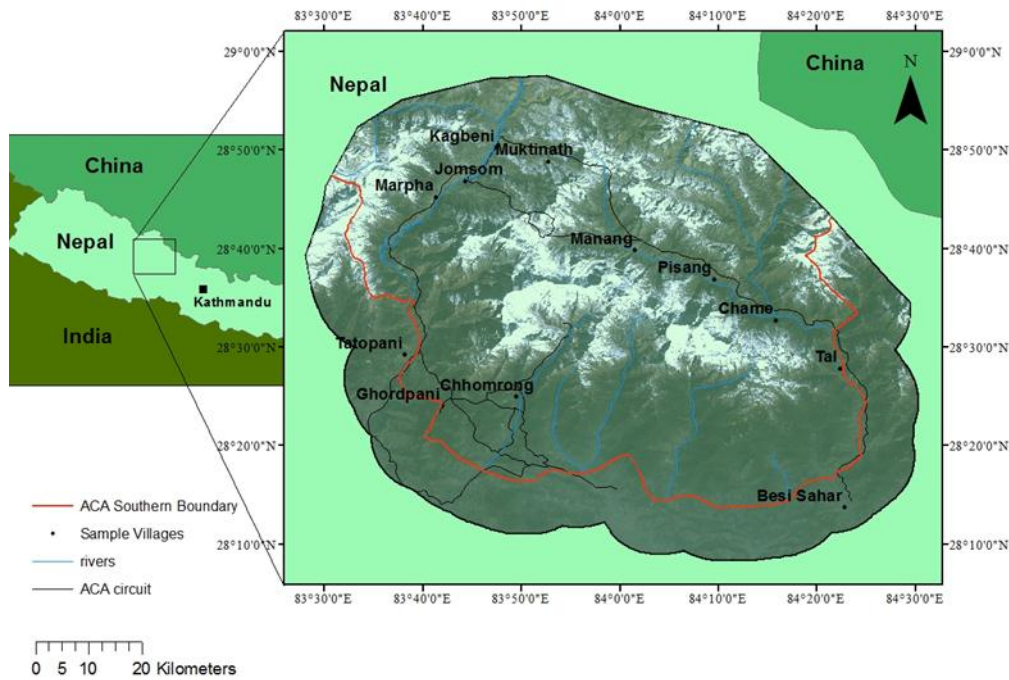


Fig. 1: Study area: Annapurna Conservation Area

The ACA is managed by the Annapurna Conservation Area Project (ACAP), which involves the local population. This is in contrast to traditional park management strategies whereby the local people are forced to relocate outside the park. The ACAP emphasises environmental education and sustainable economic development. This includes training lodge owners and the introduction of alternative energy technologies, such as kerosene burners and solar panels (Mayhew & Bindloss, 2009). There is also a system of fixed pricing for goods and services within the region to reduce competition and undercutting. To manage and oversee the project at the local level, 55 village development committees were created. The intention is to eventually hand over all responsibility for the ACAP to the local population (Chapagain, 2012).

The establishment of the ACAP has been important for addressing the many environmental and economic problems the region faces. Since historic times the Annapurna Himal has been home to a thriving population of ethnically diverse peoples involved in agriculture and trade (Bista, 1967a). The proliferation of tourism has led to a seasonal concentration of around 120,000 tourists visiting the region annually. Although deforestation was already a problem in the region before the introduction of tourism (Nepal, 2000), tourism has added to this issue due to increased demand for firewood for cooking and heating as well as for the

construction of more than 700 lodges and tea shops (Bajracharya et al., 2007). A theoretical model to explain the nature of resource use by the tourism industry is the Von Thünen model (Mather, 1986). Von Thünen's theory suggests that resource extraction decreases with increasing distance from settlements due to the costs of transport. This theory will be tested in relation to timber extraction in the ACA.

The ACAP has made a real difference to the lives of the people living inside the park. Through its community-based approach to conservation it has been able to preserve the traditional village life while encouraging more sustainable tourism practises (Nepal, 2007). However tourist visitor numbers are still increasing and despite the progress made in reducing deforestation within the park, a large number of lodge and teashop owners still rely on local forests for firewood and timber for the construction of new lodges (Nepal, 2008). Forest cover provides a number of important ecosystem services besides firewood and timber, such as habitats for biodiversity and protection against soil erosion. Erosion is a particularly important issue in the ACA because of its mountainous environment (Shrestha, 2001).

The main objective of this research is to investigate a new technique for monitoring the impacts on forest cover resulting from tourism activity in the ACA, as well as determine how successful a community-based initiative such as the ACAP can be in sustainably managing the impacts of tourism on forest harvesting in the area. The following section provides a background to land-cover mapping using remote sensing, and the opportunities created by the release of NASA's Landsat image archive. A brief overview of the main remote sensing techniques is provided, including a discussion of the issues that led to a new technique being developed for the specific research objectives of this paper. A detailed description of the method and results are provided, followed by a critical discussion on the technique.

Monitoring forest cover using remote sensing

The monitoring of forest cover using remote sensing can play an important role in determining the sustainability of forest harvesting practices and the success of a community-led initiative such as the ACAP in managing this harvesting. It is important to keep a continuous record of the state of the environment to ensure the effectiveness of any conservation efforts. However, this can be expensive and therefore cost-effective solutions are required. The recent release of NASA's archive of Landsat images to the public without charge has created the opportunity for the cost-effective use of remote sensing for monitoring forest conditions throughout the globe.

The Landsat satellite platforms have been used in a variety of studies and provide a precise and affordable data source to map and analyse land-cover change (Ahmad, 2012; Akgun et al., 2004; Firl & Carter, 2011; Knorn et al., 2009; Sader et al., 1995; Virk & King, 2006; Zăvoianu et al., 2001). The Landsat 5 Thematic Mapper (TM) and the Landsat 7 Enhanced Thematic Mapper plus (ETM+) have both been successfully used for land-cover classification and change detection analysis. These satellites have a near-polar orbit; they pass over the same point on earth approximately every 16 days and cover a swath of ground 185 km by 185 km, with a 30 m spatial resolution. These images can be downloaded from the USGS Global Visual Viewer (<http://glovis.usgs.gov>) and are provided as a matrix of digital numbers (DN) compressed to values between 0 and 256. These DN need to be converted back to reflectance values using metadata provided with the image.

When identifying forest change using two satellite images, it is important to ensure that both images are corrected for geometric and radiometric distortions. Landsat images are corrected for geometric distortions, but need radiometric corrections for variations in Earth–sun distance, solar zenith angle and sun elevation, which can be easily applied using metadata provided with the images. Atmospheric corrections for haze and moisture are also required if the image is not clear. Haze and moisture can cause spectral scattering, creating variation in the image quality. A technique for adjusting for this is called dark object subtraction (DOS) (Chavez Jr, 1988). DOS assumes that any radiation received by

the sensor from dark objects on the ground must be from atmospheric scattering rather than the dark object. The DOS technique determines the DN values for dark features in the image, such as water bodies, and subtracts this value across the whole image (Liang et al., 2001).

A difficult issue for remote sensing in mountainous regions is the shadows caused by the high relief. The Kali Ghandaki Gorge is located in the ACA between Annapurna (8078 m) and Dhaulagiri (8172 m) and is the deepest valley in the world at 2520 m (Hochgebirgsforschung, 2005). Other valleys in the ACA are also very deep and narrow, including the Modi Khola, which is the main trekking route to the Annapurna base camp (Mayhew & Bindloss, 2009). These shadows make land-cover mapping of the entire region using satellite remote sensing prone to error. There are techniques for addressing shadow problems, which include Lambertian and non-Lambertian algorithms (Law & Nichol, 2004); however, shadows are still one of the most difficult challenges of image analysis in mountainous environments.

An important contribution of this research is the trialling of a new technique that avoids this issue. As this study focuses on determining the impacts of tourism on forest cover, it is argued that a sample of the study area can be used rather than mapping the entire region. Our method therefore only samples areas free of shadow. With many land-cover mapping projects involving remote sensing, the goal is to map the entire study region and therefore this sampling approach would not work. However, the sampling approach appears rational for the objectives of this paper. The bias associated with this sampling method is discussed later in the paper.

Image enhancement using techniques such as the Normalised Difference Vegetation Index (NDVI) can improve classification results (Weishou, Ji Di, Shouguang, Haidong, & Naifeng, 2011). The NDVI produces a measure of greenness of vegetation on a continuum of values between 0 and 1, and is used to measure variations in vegetation health, density and species. An advantage of the NDVI is that it is based on a ratio of visible red and near-infrared. This band ratio value is less likely to be affected by atmospheric distortions as each band is likely to be equally affected by the distortion resulting in the ratio staying approximately the same.

There have been many forest change detection studies completed using remote sensing. Typically these studies classify the images prior to conducting change detection (Aguirre-Gutiérrez, Seijmonsbergen, & Duivenvoorden, 2012; Martínez-Verduzco, Galeana-Pizaña, & Cruz-Bello, 2012). There is now a wide range of classification techniques available, which can be divided into supervised and unsupervised classification techniques (Ahmad, 2012; Gronemeyer, 2012; Okeke & Karnieli, 2006). A supervised technique requires training data so that a spectral signature of different class types can be developed. This requires supervision to identify suitable representative areas of each class to build the spectral signatures. Once the signatures have been developed pixels can be allocated to each class based on their closeness to the signatures. Unsupervised classification uses an iterative algorithm that maximises the spectral differences between the specified number of classes required. It requires no supervision but the class types require manual labelling (Campbell & Wynne, 2011).

Increasingly, a hybrid of unsupervised and supervised classification approaches is being used (Pradhan et al., 2010). Unsupervised classification is used first, to provide an initial understanding of the potential variation in the classes available in the study area. Supervised classification is then used to specifically target classes that are important to the study. The accuracy of the change detection is highly dependent on the success of the classification (Lu, Mausel, Brondizio, & Moran, 2003). It is important to validate classification results using reference data such as maps of major vegetation types and other ground-truthed data (Bharti, RA, Adhikari, & Rawat, 2010).

The quantitative assessment of forest change is usually represented as a “to and from” change matrix, which represents each forest class that has been assessed in the study. The analysis becomes more complex when the change is being assessed in relation to a particular cause, in this case tourism activity. Forest harvesting can occur even when tourism is not present as it can be a major source of income and important for everyday living purposes. GIS analysis functions such as buffering can be used to provide forest change data samples at increasing distance from tourism activity (Rogan, Miller, Wulder, & Franklin, 2006). This can be combined with regression analysis to determine whether there is possible

relationship between proximity to tourism activity and forest change. A strong correlation can provide convincing evidence but does not necessarily prove that it is a cause (Chen, Zhao, Li, & Yin, 2006).

Method

Data

Table 1 provides the specifications for the two images used for this research, which were selected for their clarity and similar time of the year (winter), as well as being at least 10 years apart. Since 2003, Landsat 7 images have been affected by a failure of the scan line corrector resulting in 22 per cent of an image missing. For this reason Landsat 5 was chosen for 2011.

Table 1: Characteristics of the satellite data used for analysis of the study area

Satellite	Path/Row	Spatial resolution	Acquisition date	Sun elevation	Sun azimuth	Season
Landsat 7 ETM+	142/40	30 m	13/12/1999	33.61797	154.8096	winter
Landsat 5 TM	142/40	30 m	05/02/2011	37.38806	144.9072	winter

The ancillary data used in this research includes:

- photos and field notes recorded between April and May of 2012 during a trek around the study area
- Google Earth images used as reference data during the classification and validation phases of the analysis
- GIS layers of the study area, which includes roads, rivers, ecology and boundaries, and a land-cover map obtained from the International Centre for Integrated Mountain Development (ICIMOD), the European Space Agency (ESA) and the United States Geological Survey.

Field work

The field work in the ACA involved completing the Annapurna circuit and sanctuary treks, while making a detailed record through field notes and photos along the way. The photographs focused on documenting the changing forest type and the condition of the forest. Photos were also taken of the tourism operations in the villages along the treks. The field notes were a day-to-day record of the various forest types encountered and the intensity of tourism facilities present in the villages. In addition, discussions with locals and other tourists about the local environment, both past and present, as well as attitudes to the way the ACA is being managed, were also recorded. This all helped to generate a local and regional context for the research. The photos and field notes also combined to create a GIS hyperlinked catalogue of images that linked photos to their locations, which became invaluable during the classification and validation phases of the analysis.

Image preparation

Both the Landsat 7 ETM+ image from 1999 and the Landsat 5 TM image from 2011 were already rectified and geo-referenced to the Universal Transverse Mercator (UTM WGS84, Zone: 45). The accuracy of the geo-referenced images was confirmed by overlaying other GIS layers such as roads and rivers. ArcGIS software (version 10.1) was used for all the image interpretation, spatial analysis and mapping conducted for this study.

Atmospheric correction was only necessary for the Landsat 5 2011 image, in which minor haze was detected after an initial NDVI analysis showed an over-representation of high NDVI values. Dark object subtraction was used to correct this distortion.

Since images from two sensors were used for this study, Landsat 5 was calibrated with Landsat 7 using Equation 1 (Vogelmann et al., 2001). Both images were also converted to radiance using Equation 2, which adjusts for the incident angle of the sun in relation to the earth platform (Chander, Markham, & Helder, 2009), and converted to Top of the Atmosphere Reflectance using Equation 3,

which adjusts for Earth–sun distance, specific radiance emitted by the sun, and solar elevation angle (Chander et al., 2009).

$$DN7 = (\text{slope}_\lambda * DN5) + \text{intercept}$$

Where:

DN7 = the Landsat 7 ETM+ equivalent of Landsat 5 TM DN values

Slope and intercept = band-specific numbers attributed to the remote sensing platform (Vogelmann et al., 2001)

DN5 = the Landsat 5 TM DN values

Equation 1: Calibration of Landsat 5 to Landsat 7 DN values

$$L_\lambda = (\text{gain}_\lambda * DN7) + \text{bias}_\lambda$$

Where:

L_λ = the calculated radiance [in Watts / (sq. meter * μm * ster)]

gain_λ and bias_λ = band-specific numbers attributed to the remote sensing platform (Chander et al., 2009)

DN7 = the Landsat7 DN values

Equation 2: Conversion from DN to radiance

$$R_\lambda = (\pi * L_\lambda * d^2) / (E_{\text{sun}_\lambda} * \sin(\theta_{SE}))$$

Where:

R_λ = the reflectance as a unit-less ratio

L_λ = radiance value

d^2 = the Earth–sun distance in astronomical units squared

E_{sun_λ} = the band-specific radiance emitted by the sun (Chander et al., 2009)

θ_{SE} = the solar elevation angle

Equation 3: Conversion of radiance to reflectance

Image enhancement

An NDVI using Equation 4 was produced for each image, which was used in the subsequent classification process. A false colour composite image was also generated using bands 1, 4 and 5 for RGB respectively. This composite is known for highlighting vegetation, and was used to guide the classification process (University of Reading, 2002).

$$NDVI = (NIR - R) / (NIR + R)$$

Where:

NIR = near-infrared light

R = red light

Equation 4: Normalised difference vegetation index

Isolating snow and ice areas as no data

A high proportion of the study area is high alpine areas covered in snow and Ice. In general this is above the treeline and therefore not relevant to this study. Even if forest is present in these areas, the brightness of the snow and ice makes it difficult to identify forest. Snow and ice can be easily identified in satellite images because of the distinctive brightness, even if in shadow. A tasselled cap transformation based on Landsat 7 reflectance was used to calculate overall brightness (albedo) and overall wetness values within the study area (Huang, Wylie, Yang, Homer, & Zylstra, 2002). An unsupervised isocluster classification was used to identify snow and ice using both brightness and wetness.

Shadow removal

As previously stated, shadows are a major problem for remote sensing in mountainous terrain. This problem was addressed by removing the shadows rather than using topographic correction methods and the associated uncertainties. The removal of shadows changes the analysis from a complete assessment of the study area to a sample of the study area, which affects how the results can be interpreted. Rather than producing the absolute extent of forest change, the use of samples provides results that are only meaningful when interpreted as proportion (or percentage) changed.

Shadow removal was achieved by first extracting all NDVI values below a certain threshold from the images that represented shadow. Isocluster unsupervised classification was then used to isolate the spectral signatures of shadows for extraction.

An analysis mask restricting analysis to this area was then constructed from areas not in shadow or snow for both the 1999 and 2011 images. This analysis mask was used for the subsequent image classification.

Hybrid classification

Since the main objective of this study was to identify change in forest cover extent, it was not necessary to identify a number of different forest types. The change analysis therefore only required two classes: forest and non-forest, which significantly simplified the classification process. The final classification process was derived from an iterative procedure of trial and error, which resulted in a combination of isocluster unsupervised and maximum likelihood supervised classification techniques being used to identify these two classes. The final process required first converting the images to NDVI images and then applying unsupervised classification to 15 different unidentified classes. These 15 classes were subsequently identified using a combination of the field photos and notes, GeoEye Google Earth images, and the false-colour composites images. These 15 classes covered the main forest and non-forest types found in the study area.

Signature files were then generated using the unsupervised classifications as the source data for the training polygons. The training polygons sampled all classes of forest and non-forest identified from the unsupervised classification. The last step in the process was to perform supervised classification on both NDVI images using these signature files.

Accuracy assessment

Accuracy assessment was conducted with both quantitative and qualitative methods. The quantitative method utilised the error matrix method, which provided user accuracy, producer accuracy, overall accuracy and the Kappa statistic (Jensen, 2005). This method compares ground-truthed reference data with the remote sensing-derived data, and was applied to just the 2011 classification results. It was not possible to provide an error assessment of the 1999 classification as reference data is not available. The referenced data was mainly obtained from 2012 using Google Earth's historical archive. Although GeoEye images are not strictly ground-truthed, they provide high-quality images that are easy to interpret. This interpretation was combined with field notes and photos taken in the field. Some of the photos were hyperlinked to points on the forest increase and decrease map in Figure 3 to allow an assessment of the change

detection on point by point bases. The sample for the error matrix initially consisted five hundred random points, generated by using ArcGIS (“create random points” tool). Many of these points were located over no-data areas and were eliminated resulting in 394 random sample points being used. These points were converted to a KML file and loaded into Google Earth so that they overlaid with the GeoEye image to assist interpretation and manually classified as forest or non-forest.

Forest change detection in relation to tourism sites

The two classified images were compared using the “combine” tool to create a layer identifying where forest has been removed and where forest has been added. From this forest change layer, area statistics were generated providing insight into the whole study area.

To assess the impacts from tourism, twelve villages known to accommodate many tourists were identified using the field notes as a guide and spatially located as a point GIS layer. These points are referred to as tourism facilities as they are not strictly tourism villages as many local people live in these villages. A gradient of tourism proximity was generated using the ArcGIS “multi-ring buffer” tool to produce ten concentric circles placed 1km apart around each of the tourism facilities. The proximity zones were then overlaid with the forest change layer, and statistics along with the area of forest added and removed were produced for each tourism facility and proximity zone. This was further analysed to calculate the net percentage change in forest, and regression analysis was used to identify trends in forest removal and tourism proximity. This analysis was applied using all tourism facilities combined, the front (southern) country facilities, the back (northern) country facilities, as well as each individual facility.

Results

Overall changes

Figure 2 shows the forest classifications produced for both 1999 and 2011 Landsat images, and Figure 3 shows the areas of forest addition and removal. Table 2 provides the areas of each class. The total area of the study area was 701,698 ha however a total of 292,278 ha removed from the analysis due to shadows (136,022 ha) and snow and ice (195,432 ha). The total area classified for forest

and non-forest was 409,420. From Figure 2, it is clear that most of the forest that could be identified is in the southern part of the study area, which has lower elevation and higher rainfall. This area has larger trees suitable for timber production and is closer to major urban areas, such as Pokhara. In this area there has also been forest added but this is less than what has been removed. In the drier northern region, Figure 2 shows that more forest has been added than removed but the extent of this change is small compared to the changes in the south. The spatial analysis in relation to tourist facilities confirms this.

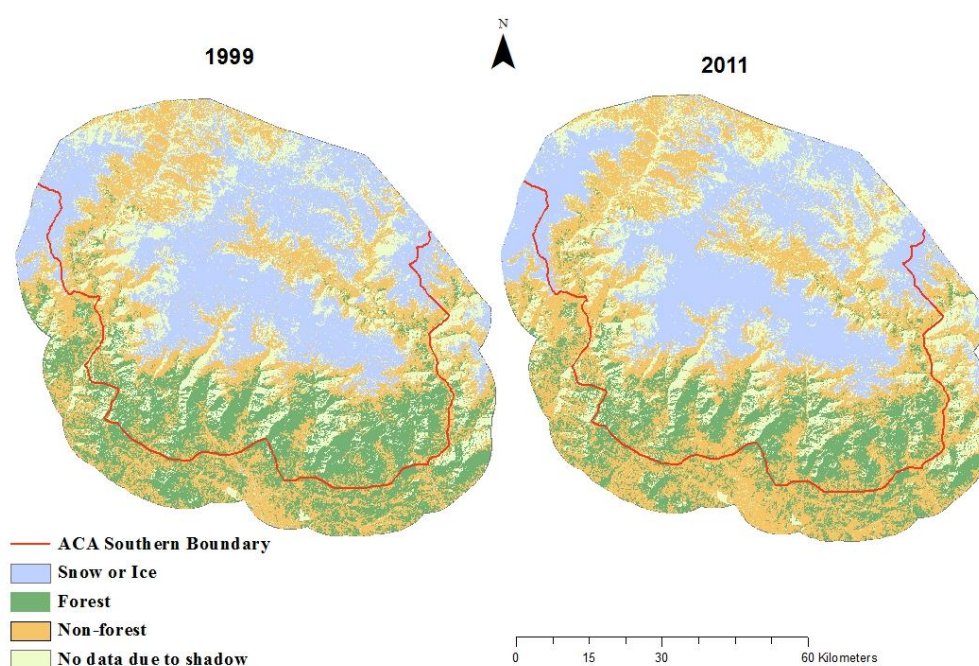


Fig. 2: Forest and non-forest areas for 1999 and 2011

Based on the overall area analysed there has been a net decrease of forest of 8 per cent. However, as shown in Table 3, the total reduction in forest was 10 per cent but new forest was added to non-forest areas (2 per cent). Twenty-nine per cent of the area analysed was forest. If it is assumed that the proportion of forest is the same in the shadowed areas as the non-shadowed areas, then the total area of forest in the study area is 157,943.3 ha, and therefore the estimated removal of forest for the whole study area is 42,524.5 ha, which excludes any potential forest in the snow and ice areas.

Table 2: Forest and non-forest areas for 1999 and 2011

	1999		2011		Net change (ha)	Net Change (%)
	Total area (ha)	Total area (%)	Total area (ha)	Total area (%)		
Forest	152 603	37	118 497	29	−34,106	−8
Non-forest	256817	63	290923	71	34,106	8

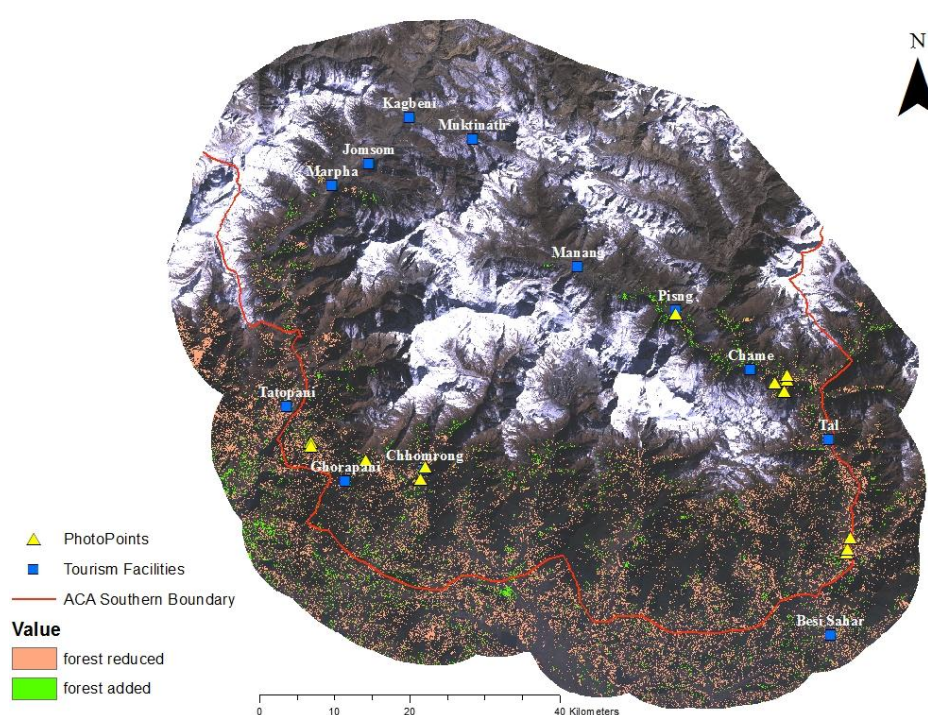


Fig. 3: Increase and decrease in forest cover

Table 3: Types of changes between 1999 and 2011 for areas analysed

Change type	Area (Ha)	(%)
Non-forest to forest	6,502	2
Forest to non-forest	40,609	10
Forest; no change	111,995	27
Non-forest; no change	250,315	61
Total sample area	409,420	100

Accuracy assessment

Table 4 specifies the user accuracy for forest as 86 per cent and non-forest as 93 per cent. This indicates that 14 per cent of forest and 7 per cent of non-forest were not included in the classification. The producer accuracy for forest was 94 per cent, indicating that 6 per cent of the forest cover was incorrectly assigned to non-forest; while non-forest producer accuracy was 84 per cent, showing 16 per cent of non-forest was incorrectly assigned to forest. The distribution of errors of omission appears to be towards non-forest while the distribution of errors of commission is towards forest. This indicates that both forest and non-forest land covers have been overestimated to a small degree. The overall accuracy indicated that 89 per cent of the classification is correct, while the Kappa statistic shows a 78 per cent moderate agreement between the classified data and the ground-truthed reference data.

Table 4: The error matrix showing producer and user error

Classified data	Reference data			User accuracy
	Forest	Non-forest	Total	
Forest	185	31	216	86
Non-forest	12	166	178	93
Total	197	197	394	
Producer accuracy	94	84		
Overall accuracy	89			
Kappa	0.78			

Impacts of tourism on forest extent

Table 5 summarises the changes in forest extent by proximity for all 12 tourism facilities, as well as grouping them by north and south, and all combined. Interestingly, there is a reduction in forest of 22.2% and 20.2% for 0-5km and 6-10 km respectively. This is higher than the overall forest reduction (8%) calculated for the whole study area analysed. It could be concluded from this that tourism villages do have an impact on the forest, however, there is considerable geographical variation in the forest impacts of these villages as shown in Table 5. In general the northern villages have had an increase in forest and the southern forest have had decrease in forest. Some villages, such as Manang and Kagbeni have had a high percentage increase in forest but the area increase is small.

Overall there does not appear to be an increase in forest reduction due to close proximity to the villages as shown Table 5 using 0-5km and 6-10km intervals but also graphed in Figure 4 in more detail using 1km intervals and a trend line. But again there is considerable variation geographically. Figures 5 and 6 illustrate the trends of the northern and southern villages respectively. There are opposite trends between the northern and southern villages. For the northern villages, areas close to villages have had an increase in forest while for the southern villages these areas have had the highest forest reductions.

Table 5: Net forest change summary table

0–5 km from villages								6–10 km from villages						
Village	Village sample area (ha)	Total forest area in sample		Forest added (ha)	Forest removed (ha)	Net change		Village sample area (ha)	Total forest area in sample		Forest added (ha)	Forest removed (ha)	Net change	
		1999 (ha)	2011 (ha)			(ha)	(%)		1999 (ha)	2011 (ha)			(ha)	(%)
Southern villages														
Besi Sahar	7 038.7	3 792.8	2 837.2	115.1	1 094.4	–979.3	–25.8	13 472.1	9 056.2	7 427.3	279.0	1 907.9	–1 628.9	–18.0
Tal	5 155.4	1 710.5	1 128.1	99.2	667.0	–567.8	–33.2	14 447.6	5 326.7	3 800.3	485.7	1 377.2	–891.5	–16.7
Chame	5 902.5	766.4	661.2	152.3	257.4	–105.1	–13.7	16 717.2	1 207.2	1 007.2	197.0	397.0	–200.0	–16.6
Tatopani	6 334.3	3 288.1	2 069.9	133.8	1 352.0	–1 218.2	–37.0	17 031.1	8 487.6	5 763.1	343.4	3 068.0	–2 724.6	–32.1
Ghordpani	5 712.5	4 630.8	3 878.6	76.4	828.5	–752.1	–16.2	18 556.9	11 829.0	9 415.2	446.9	2 860.7	–2 413.8	–20.4
Chhomrong	5 902.5	4 385.2	3 703.9	141.2	822.5	–681.3	–15.5	16 717.2	9 195.1	7 783.1	279.9	1 691.9	–1 412.0	–15.4
All southern villages	36 045.8	18 573.6	14 279.9	718.0	5 021.8	–4 303.8	–23.2	96 942.2	45 101.7	35 196.1	2 031.9	11 302.7	–9 270.7	–20.6
Northern villages														
Pisang	4 223.1	281.3	406.2	156.6	31.7	124.9	–44.4	9 215.2	454.7	507.5	187.4	134.6	52.8	11.6
Manang	4 177.4	16.0	37.4	24.5	3.1	21.4	133.7	8 548.3	26.8	78.3	57.4	5.9	51.5	191.9
Muktinath	3 562.9	0.0	0.0	0.0	0.0	0.0	0.0	8 802.5	0.8	0.7	0.6	0.7	–0.1	–11.1
Kagbeni	8 575.7	9.3	26.0	17.7	1.0	16.7	180.6	21 986.1	15.3	23.7	14.8	6.4	8.4	54.7
Jomsom	5 255.9	127.2	98.2	29.5	58.5	–29.0	–22.8	12 160.4	281.5	177.1	38.4	165.1	–126.6	–45.0
Marpha	5 122.4	361.9	229.0	45.3	–1 78.2	–132.9	–36.7	11 423.9	446.1	372.1	104.1	178.2	–74.1	–16.6
All northern villages	30 917.3	795.6	796.8	273.6	272.4	1.2	0.1	72 136.4	1 225.3	1 159.4	402.8	490.9	–88.1	–7.2
All villages	66 963.2	19 369.2	15 075.6	991.6	5 294.3	–4 302.6	–22.2	169 078.5	46 327.0	36 355.5	2 434.7	11 793.5	–9 358.8	–20.2

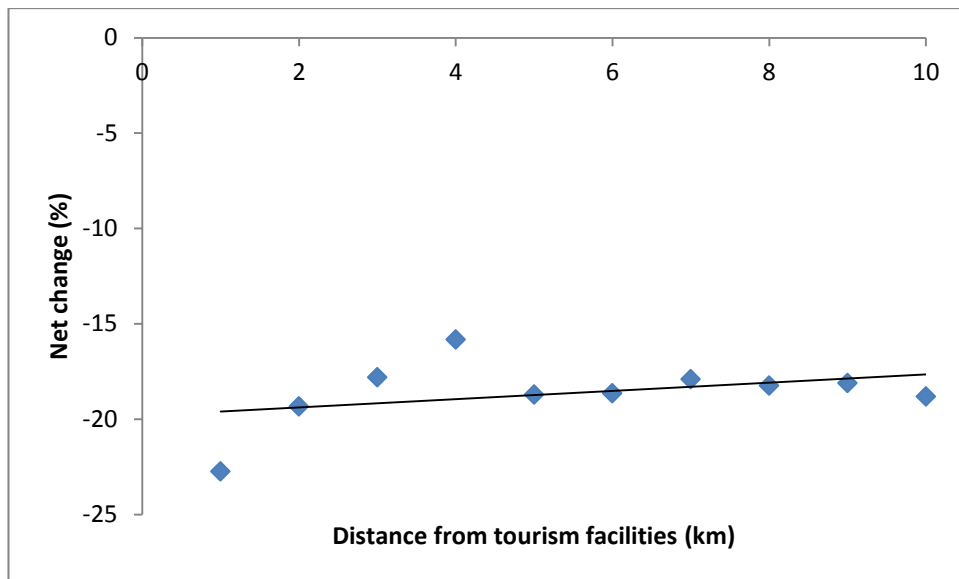


Fig. 4: Total Net change in forest area around all tourism facilities
 (cf. = 0.1871, $r^2 = 0.491$)

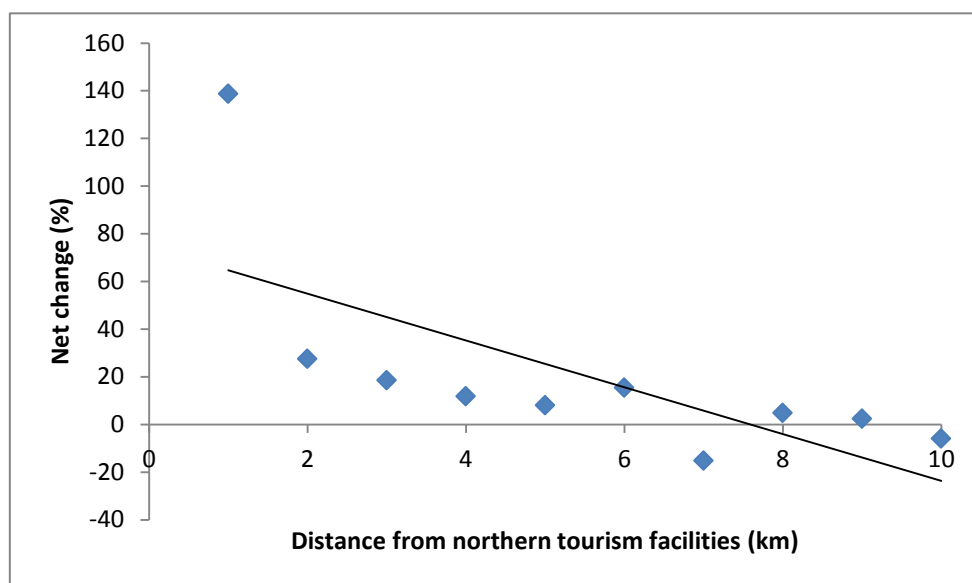


Fig. 5: Net change in forest area around Northern tourism facilities
 (cf. = 9.8174, $r^2 = 0.472$)

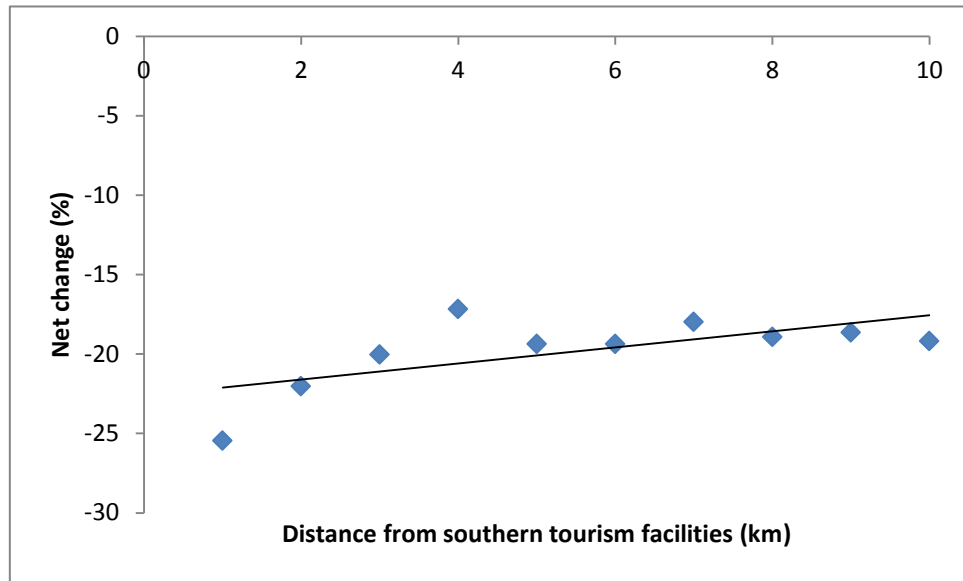


Fig 6: Net change in forest area around southern facilities
(cf. = 0.5053, $r^2 = 0.42$)

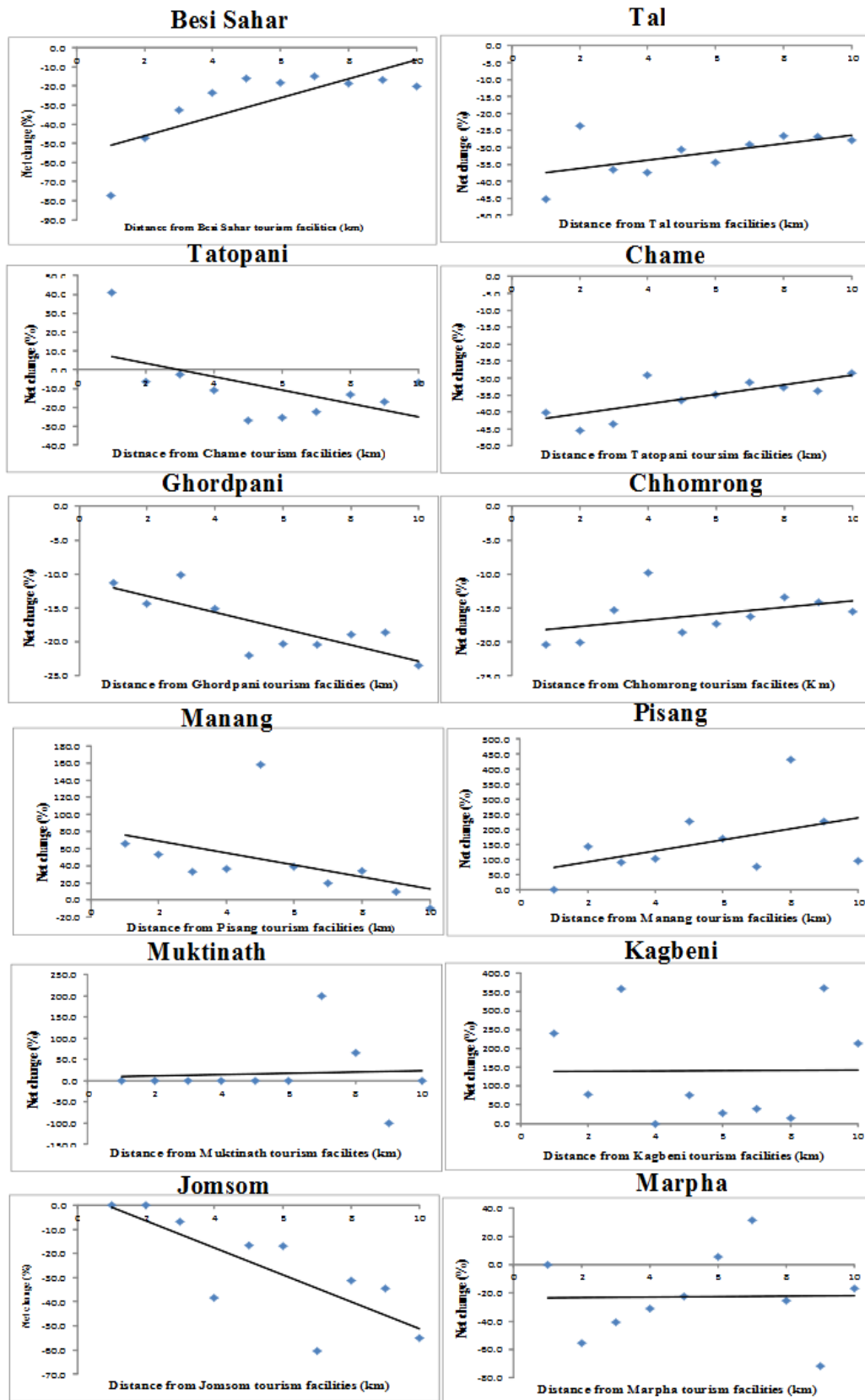


Fig. 7: Net change in forest area around individual tourism facilities

Figure 7 displays both positive and negative relationships in regard to the trend of forest addition or removal from the sample areas. A positive trend equals decreasing forest removal at greater distance from a settlement, which is in line with Von Thünen's model of resource use, while a negative relationship signifies increasing forest removal at greater distance from settlements. The first six villages represent the southern tourism facilities. There is great variation among these samples. Besi Sahar is located at the start of the Annapurna circuit and is a relatively large town with plenty of visitors and through traffic from trekkers, which explains the high level of forest removal, although the trend line has a positive relationship indicating decreasing forest removal at greater distance from the settlement. Tal and Chame also show the same positive relationship as Besi Sahar, suggesting that forest removal decreases over distance and that close proximity to tourism facilities increases forest harvesting. The level of forest removal, however, is still high in these areas. Tal and Chame are both in areas with little agriculture, suggesting that tourism is the primary reason for harvesting of the forest. There has also been recent road development in this area allowing tourists to reach Tal and Chame much faster than in the past. Tatopani, Ghordpani and Chhomrong are in an area of agricultural development as well as being the three settlements in the sample at the eastern end of the Annapurna circuit, which is close to Pokhara and is a starting point for many trekkers. Tatopani and Ghordpani have trend lines indicating a negative relationship, representing an increase in forest removal with increasing distance from both settlements. Chhomrong, however, has a positive relationship, indicating less forest removal away from the settlement. Chhomrong is located at the start of the Annapurna sanctuary trek and harvesting of forest is more restricted in this region, which may account for trend around Chhomrong. For Tatopani and Ghordpani, the negative relationship maybe due to the location of the agricultural land being in the outer proximity zones around both settlements. In the case of Tatopani it is harder to say; it is surrounded by cliffs and during field work it was difficult to see what land covers were around further away. However, the use of fire to clear forest was observed very close to Tatopani, indicating agriculture development may be occurring nearby.

The northern tourism facilities represented by the last six graphs in Figure 7 display forest addition, such as in the case of Pisang and Manang. The northern tourism facilities are located in a dry region with less forest, except for the area around Pisang, which has experienced the highest increase in forest of all the samples, particularly in proximity zones beyond 5 km. The trend line shows a positive relationship indicating increased harvesting of forest nearer Pisang. The other five facilities illustrate both positive and negative relationships regarding tourism forest harvesting. Jomsom, on the northern end of the Kali Gandaki valley, is a special case in that it has an airport as well as being on the main road. This has allowed Jomsom to grow into one of the largest settlements in the region with potentially as much through traffic from trekkers and other tourists as Besi Sahar. Jomsom is also located relatively close to Marpha, which means the sample areas of Jomsom and Marpha overlap. Consequently the negative relationship indicated by the trend line exhibits a high level of forest removal, some of which may be occurring due to the influence of the other tourism facilities at Marpha.

Around Manang and Kagbeni there is forest increase. The trend for Manang demonstrates a positive relationship with decreasing forest harvesting in the outer proximity zones. Kagbeni on the other hand illustrates a near neutral relationship as the trend line is almost horizontal. This is due to inconsistent forest addition and removal. This could be attributed to plantations of forest at various distances from the village, planted as part of ACAP conservation efforts, as well as orchards of trees close to the village. Muktinath and Marpha both have a pattern of a small increase in forest in the outer proximity zones, which represents forest cover beyond the alpine desert that surround both Muktinath and Marpha. This may be an indication of a positive relationship relating to the expected resource use trend of decreasing harvesting over greater distance but is more likely a result of changing climate from alpine desert to temperate alpine forest. Given the variable nature of these results it is difficult to make a clear link between the patterns net change to tourism. However, figures 4 to 7 and Table 5 give a clear indication of the geographic variation in net change between the northern and southern tourism facilities.

Discussion and conclusions

Impact of tourism

This research provides evidence that the impact of tourism on forest cover varies geographically. In most northern areas, forest extent increased with closer proximity to tourism facilities while in southern areas tourism facilities appear to be associated with a decrease in forest extent. However, this research cannot prove that this change is caused directly by tourism as there are other causes that have not been controlled for in the analysis. This includes activities such as agriculture expansion, and timber harvesting for export outside the region. The analysis does control for access by comparing the isolated northern regions with the more accessible southern regions. It appears that access to larger markets does result in increased forest harvesting. Another reason for the difference in forest change between the northern and southern regions is that the southern region was only partially in the ACA, while the northern region was completely enclosed within the ACA. This means that there are tighter controls on forest clearance in the northern region. The forest type also varies between these regions due to elevation and climate. The northern forests are less suitable for timber extraction, but are slower growing and are used for firewood.

The high variability in forest extraction in relation to proximity to tourism facilities shows that Von Thünen's model of increased resource extraction close to settlement (Mather, 1986) is an over-simplification. The results do not reflect Von Thünen's model for many of the villages assessed, although the model may not have been intended for conservation areas such as those assessed in this research. Von Thünen's model, however, may explain the difference between the northern and southern regions, as the southern region, which had higher forest extraction, is closer to major settlements. Von Thünen's model may also account for the positive relationships towards decreasing forest removal further from settlements found mainly in the southern villages that indicates tourism was having an effect on forest cover in these localised areas.

Method: limitations and implications

This study has demonstrated that remote sensing can provide a cost effective method for monitoring forests and other natural resources, and is ideal for developing countries with low budgets. Using remote sensing-derived information as a resource management tool would allow policy makers to see areas within the ACA that are under threat due to excessive harvesting of the forest. However, community groups in the study area would have difficulty conducting such remote sensing research due to limitations in expertise, and availability of basic infrastructure, such as electricity, high speed internet access and modern computers. However, such analysis is possible using internationally funded agencies such as ICIMOD that are located in the main cities in Nepal, who do have the facilities and infrastructure.

The relatively coarse spatial resolution of the Landsat images is a limitation of this research, although the error determined through ground-truthing was at an acceptable level. Higher resolution images that are cheap will likely become available in the future, but to build a useful archive of images comparable to the Landsat archive could take at least a decade.

This research has revealed that problems caused by shadows can be avoided by using sample areas free of shadow. This works for a focused research question, such as what impact has there been on the forest, but would not work for broad land-cover mapping. There are many such focused research questions that could use this sampling technique: assessing change in glacier extents, snowfall, water quality monitoring, urban sprawl and crop condition. It is important to note that taking a sampling approach limits the conclusions that can be made from this analysis. Therefore forest change that has occurred outside the sample can only be inferred. Trying to include shadow areas risks compromising the analysis, especially in highly mountainous areas. The shadow removal method has the potential bias of forest types with high NDVI values being selected over forest types with low NDVI values. Higher NDVI values often have a correlation with healthier, more productive forest. This could mean that within shadowed areas there may be forests that are not frequently harvested due to their slow growth. Thus addition of forest in these areas may be occurring. In general the low-NDVI

values that were extracted as part of the shadow removal were all verified as corresponding to shadows detected in the composite false-colour images as well as the unsupervised classifications also used to isolate and identify shadows. Therefore the NDVI values that were removed were unlikely to have provided any useful data.

This research has also substantiated the use of the hybrid classification technique that combines unsupervised and supervised classification, although this was only tested on forest and non-forest classes. Choosing to only focus on forest and non-forest was effective, as forest was the environmental indicator chosen for this study. This did nevertheless limit what could be observed in terms of what other land covers were replacing forest cover. The use of an NDVI image was also shown to be beneficial, especially since it helps reduce the effect of atmospheric distortion.

Combining remote sensing with GIS analysis has been shown by this research to be useful for exploring spatial relationships between phenomena. In this case proximity zones were constructed to produce a gradient of tourism activity which could be analysed using regression analysis. The calculation of proximity gradients is a widely used tool for exploring spatial relationship for a range of geographical enquiries. The most famous example is Snow's analysis of cholera outbreaks and water pumps. Our research has shown how this proximity analysis can be applied to tourism, and addresses a widespread problem associated with resource extraction and development. Monitoring using remote sensing and proximity analysis can be a powerful deterrent for illegal resource extraction.

Future research

Future research could apply the techniques established in this research for environmental monitoring. It would be appropriate to use GIS, remote sensing and the Landsat archive for environmental monitoring in highly populated mountainous regions. Community-based conservation, such as that used in the ACAP, is a model many developing nations have adopted. Another example of the use of this model is in the Amazon Andes region of Peru, where three private conservation areas have been established by community groups (Butler, 2012).

The three parks only cover 18,882 ha, but this includes a wide range of habitat such as high altitude grassland, cloud forest and rainforest. They were established with the help of the Amazon Conservation Association, which employs local people for ecological restoration and monitoring of the forest for logging and fire damage. In time ecotourism may also become part of the local economy (Butler, 2012). Because the Landsat archives have a record of images from all over the planet going back to the 1970s, it would be possible to conduct similar research in any mountainous environment.

Future research could include higher resolution data, elevation data and a comparison of the standard methods of topographic correction, as well as comparing the standard techniques with modified shadow and cloud removal methods. The classification of other land cover in more detail would also be worth exploring. This would identify possible land-use changes, other than harvesting by tourism operators, which could be responsible for the forest cover change that occurs. A different form of proximity analysis could also be used for the post classification change detection. Instead of creating multiple ring buffer zones around points, linear proximity analysis using multiple ring buffer zones around linear features such as road, power lines and tracks like the Annapurna circuit could provide better insight on causal factors of deforestation and general land-cover change. Further research on the ACA is also important as it is a region experiencing increasing development, particularly in regard to infrastructure such as roads and power stations. How this will change both the tourism industry and the environment in the region is uncertain, but satellite remote sensing analysis is an ideal tool for monitoring these changes.

Chapter 5: Discussion

5.1 Impact of tourism

This research provides evidence that the impacts of tourism on forest cover varies geographically. In most northern areas, forest extent increased with closer proximity to tourism facilities while in southern areas tourism facilities appear to be associated with a decrease in forest extent. However, this research cannot prove that this change is caused directly by tourism as there are other causes that have not been controlled for in the analysis. This includes activities such as agriculture expansion and timber harvesting for export outside the region. The analysis does control for access by comparing the isolated northern regions with the more accessible southern regions. It appears that access to larger markets does result in increased forest harvesting. Although another reason for the difference in forest change between the northern and southern regions is that the southern region was only partially in the ACA, while the northern region was completely enclosed within the ACA. This means that there are tighter controls of forest clearance in the northern region. The forest type also varies between these regions due to elevation and climate. The northern forests are less suitable for timber extraction, but are slower growing and used for firewood.

The high variability in forest extraction in relation to proximity to tourism facilities shows that Von Thünen's model of increased resource extraction close to settlement (Mather, 1986) is an oversimplification. The results do not reflect Von Thünen's model for many of the villages assessed, although the model may not have been intended for conservation areas as assessed in this research. Von Thünen's model, however, may explain the difference between the northern and southern regions, as the southern region, which had higher forest extraction, is closer to major settlements. Von Thünen's model may also account for the positive relationships towards decreasing forest removal further from settlements found mainly in the southern villages that indicates tourism was having an effect on forest cover in these localised areas.

5.2 Benefits and limitations of the method

This study has demonstrated that remote sensing can provide a cost-effective method for monitoring forests and other natural resources, and is ideal for developing countries with low budgets. Using remote sensing-derived information as a resource management tool would allow policy makers to see areas within the ACA that are under threat due to excessive harvesting of the forest. However, it would be difficult for community groups in the study area to conduct such remote sensing research, due to limitations in expertise, availability of basic infrastructure such as electricity, high-speed internet access and modern computers. However, such analysis is possible using internationally funded agencies such as ICIMOD, which are located in the main cities in Nepal and do have the facilities and infrastructure.

This research has revealed that problems caused by shadows can be avoided by using sample areas free of shadow. This works for a focused research question, such as what impact has there been on the forest, but would not work for broad land cover mapping. There are many such focused research questions that could use this sampling technique. This includes assessing change in glacier extents, snowfall, water quality monitoring, urban sprawl and crop condition. Trying to include shadow areas risks compromising the analysis, especially in highly mountainous areas. Shadow removal was chosen over other methods due to issues relating to the under- and over-corrections that can occur using traditional topographic correction, as well as the uncertainties relating to the effect of the quality of the DEM on the correction results (see Chapter 3). These issues led to the more cautious sampling approach to ensure the reliability of the data. It is important to note that taking a sampling approach limits the conclusions that can be made from this analysis. Forest change that has occurred outside the sample can only be inferred.

This research has also substantiated the use of the hybrid classification technique that combines unsupervised and supervised classification, although this was only tested on forest and non-forest classes. The decision to focus on forest cover rather than classify all land-covers together was made because forest cover was the environmental indicator chosen to test the effects of tourism on the

environment of the ACA, due to the close link between harvesting of forest and the industry. Therefore issues with spectral confusion between barren land, urban land and water could be avoided. The use of NDVI images was shown to be beneficial as they reduce the effect of atmospheric distortion. The opportunity cost of only focusing on forest cover was that the transition to other land covers such as agriculture and barren land from forest is not illustrated. This extra information would give analysts more insight into the possible causes of the land-cover change based on the wider economic and environmental conditions in the study area.

The accuracy assessment methods used in this research achieved both qualitative and quantitative measures of the accuracy of the analysis. The visual method using hyperlinked photo points helped to refine the classification and change detection analysis when the results did not match the photos. Unfortunately, opportunities for photography were restricted to the Annapurna circuit and it was not possible to take photos at the locations of the random sampling points used for the error matrix, limiting the utility of the photo record produced in the field. The error matrix produced statistics that indicated there were small errors with the forest classification but overall validated the classification.

Combining remote sensing with GIS analysis has been shown by this research to explore spatial relationships between phenomena. In this case, proximity zones were constructed to produce a gradient of tourism activity which could be analysed using regression analysis. The calculation of proximity gradients is a widely used tool for exploring spatial relationship for a range of geographical enquiries. The most famous example is Snow's analysis of cholera outbreaks and water pumps (Stevens, 1993).

Our research has shown how this proximity analysis can be applied to tourism, and addresses a widespread problem associated with resource extraction and development, although the model was limited by the variability of the data and the assumption of a maximum distance from a central market that resources would be extracted. Nonetheless, monitoring using remote sensing and proximity analysis can be a powerful deterrent for illegal resource extraction.

5.3 Future research

Future research could apply the techniques established in this research for environmental monitoring. It would be appropriate to use GIS, remote sensing and the Landsat archive for environmental monitoring in highly populated mountainous regions. Community-based conservation, such as that used in the ACAP, is a model many developing nations have adopted. Another example of the use of this model is in the Amazon Andes region of Peru, where three private conservation areas have been established by community groups (Butler, 2012). The three parks only cover 18,882 ha, but include a wide range of habitats such as high altitude grassland, cloud forest and rainforests. They were established with the help of the Amazon conservation association which employs local people for ecological restoration and monitoring of the forest for logging and fire damage. In time, ecotourism may also become part of the local economy. Because the Landsat archives record images from all over the planet going back to the 1970s, it would be possible to conduct similar research in any mountainous environment.

Any future research should include higher resolution data, elevation data and a comparison of the standard methods of topographic correction, as well as comparing the standard techniques with modified shadow and cloud removal methods. The classification of other land-covers in more detail would also be worth exploring. This would identify possible land-use changes, other than harvesting by tourism operators, that could be responsible for the forest cover change that occurs. A different form of proximity analysis could also be used for the post classification change detection. Instead of creating multiple ring buffer zones around points, linear proximity analysis using multiple ring buffer zones around linear features such as road, power lines and tracks like the Annapurna circuit could provide better insight on causal factors of deforestation and general land-cover change. Further research on the ACA is also important as it is a region experiencing increasing development, particularly in regard to infrastructure such as roads and power stations. How this will change both the tourism industry and the environment in the region is uncertain, but satellite remote sensing analysis is the ideal tool for monitoring these changes.

Chapter 6: Conclusion

6.1 Research themes

One of the major themes of this research was the model of community-managed conservation areas. To test the effectiveness of that initiative, the following major research objectives were formulated:

- To detect forest cover change in the Annapurna conservation area.
- To look at the relationship between distance from main tourism centres and the percentage change in forest area.
- To review different methods of image classification and change detection that could be used in future remote sensing environmental monitoring projects set up by ACAP.

To put the analysis in context, a discourse of tourism literature was also produced that reviewed the development of mountain tourism in Nepal (specifically in the ACA) and its consequences. By using forest mapping, it was discovered that the community-based conservation method employed by the ACAP had been to control deforestation but not prevent it. Linking this deforestation to tourism through proximity was difficult as, although forest cover change was detected, limitations in the methodologies explained in Chapter 5 did not account for other factors that could cause deforestation. The methods that were developed did, however, demonstrate the utility of free remote-sensing data combined with ancillary data in a GIS system for groups wanting to do environmental monitoring with a limited budget.

6.2 Implications of methods for geography and remote sensing

Geography is a study of the interactions between the natural and cultural environment, and remote sensing provides a tool that allows researchers to monitor and understand those interactions on a range of scales. Considering the methods used in this research, two stood out in relation to standard remote sensing techniques and their applications in geography research in land cover

change: the use of shadow removal for topographic correction and the use of proximity analysis to illustrate a relationship between forest cover change and tourism activity.

As described in Chapter 5, the shadow removal technique forces the analyst to take a sampling approach to the research. Sampling is a technique often used in social geography, whereby a researcher will canvas a community using surveys and interviews to gain insight into a specific issue. In remote sensing a form of sampling does occur through spectral analysis techniques such as NDVI or tasseled capped transformations, which display specific aspects of remote sensing images of forest, ice or snow. These spectral analysis techniques are generally measures of intensity and, unlike land-cover change detection methods, they do not quantify changes in terms of land area. Future application of the shadow removal method can allow researchers to move to a more sample-based approach to land-cover change detection, giving them the freedom to avoid topographic distortion in their data and the uncertainties inherent in traditional topographic correction methods.

As mentioned in Chapter 5, proximity analysis is commonly used in geography. Remote sensing also has a history of using proximity analysis; for example, a study done in Spain used areas identified as fire hazards and compared them with images of past fire damage to find a relationship (Chuvieco & Congalton, 1989). Unlike a comparison of fire damage and known areas of fire risk, tourism and deforestation have less obvious effects that can be observed, as deforestation has many causes. Though the results in this research had their limitations, there is room for proximity analysis to be used with variables other than tourism facilities, such as the border of the ACA or the Annapurna circuit track, which could each provide more insight to the distribution of deforestation and its causes in the ACA. The implication of this research is that proximity analysis can show a relationship between variables such as tourism activity and forest change and that it can be a powerful tool for showing relationships in remote sensing analysis.

6.3 Implications of findings

The ultimate implication of the findings in this research would be a change in the management policies of the ACA. The use of remote sensing-derived information as a resource management tool would allow policy makers to see areas within the ACA that are under threat due to excessive harvesting of the forest. It is clear that without the conservation measures taken by ACAP the deforestation within the ACA would be much worse. As the region continues to change, the management of ACAP and the local community groups will need up-to-date information about how the forest is changing and what areas are at risk. Therefore it is likely that ACAP will seek remote sensing information to monitor the ACA environment in the future. They may even perform their own analysis although, as mentioned in Chapter 5, this would be problematic due to limitations in expertise and availability of basic infrastructure. However with international agencies such as ICIMOD and free data sets like NASA's Landsat archive, continual monitoring of the ACA environment using remote sensing is possible. Should community committees and the administration of the ACAP want to undertake this work, they should seek out GIS and remote sensing professionals in organisations such as universities and ICIMOD who are willing to volunteer their time, resources and data to produce research for environmental monitoring.

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